A TWO-VEHICLE TRAFFIC SIMULATION FOR CONGESTED ROADS USING POTENTIAL FIELDS

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MARCH, 1995

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A Thesis Submitted
In Partial Fulfilment of the Requirements
for the Degree of
MASTER OF TECHNOLOGY

by
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to the
DEPARTMENT OF MECHANICAL ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY, KANPUR
March, 1995

CERTIFICATE

This is to certify that the thesis entitled **"A TWO-VEHICLE TRAFFIC SIMULATION FOR CONGESTED ROADS USING POTENTIAL FIELDS"**, by *Shami Gupta*, Roll No. 9310535, has been carried out under my supervision and has not been submitted elsewhere for award of a degree.

March, 1995

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ACKNOWLEDGEMENT

I hereby express my deep gratitude and sincere regards to my thesis supervisor, Dr. Amitabha Mukerjee for his constant inspiration, encouragement and guidance at every stage of my work - right from selection of the topic to the submission of the present document, and also at personal level - outside the premises of my thesis. I would remember his purposeful suggestions to pull me out of the "local minima" where I had been stuck helplessly midway through my work.

My regards are also due to Dr. Partha Chakroborty for his valuable suggestions over various minute aspects in relation to the current thesis. I would like to thank everybody in the Centre For Robotics for providing me a wonderful environment to work.

Last but not the least, my regards are due to all my friends who made my stay in IIT Kanpur a memorable one.

March, 1995

Shami Gupta

ABSTRACT

This thesis deals with planning the motion of two vehicles in congested roads with multiple turns and closely spaced crossings. Each vehicle-driver system is modelled as a separate entity with varying characteristics such as aggressiveness, position in the lane, braking ability, belief of other driver's behaviour etc. In contrast to search-based techniques, a potential field approach is used to plan a path based on a 3-dimensional Configuration Space. "Local minima" are reduced by "looking ahead" from the present situation based upon driver's nature and belief. Kinematic (Nonholonomic) and Dynamic constraints are taken into account to generate physically realistic path. The model has been studied for a number of test cases involving crossing, overtaking, turning and independent motion.

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Chapter 1

Introduction

1.1 The Two Vehicle Problem

Modelling traffic flow in Indian conditions is a difficult yet important problem. Models of car-following, which form the basis of traffic flow are inadequate in India. Extraneous factors like flow interruptions due to cross traffic, narrow lane widths, unequal lane widths due to variable encroachment, apathy towards traffic regulations, and highly varying vehicle characteristics (from bullock carts to compact cars) contribute towards the uniqueness of Indian traffic conditions. In spite of the apparently chaotic situation of Indian roads, traffic has to be modelled, and that too at the microscopic level so as to develop realistic simulations of Indian traffic conditions.

In order to develop a microscopic model one must first understand the interactions between pairs of vehicles, interaction between a vehicle and road features, and then introduce additional vehicles. One of the first objectives then is to simulate a two vehicle interaction with the environment and exhibit behaviour conforming to typical Indian traffic conditions.

In this work, the interaction of two vehicles are modelled and studied for different cases e.g., vehicles approaching each other, vehicles moving in the same directions, vehicles in independent tracks (i.e., lanes) and also for different vehicle-

types. A typical road situation is indicated in Figure 1.1 with the tracks by which the two vehicles are supposed to travel.

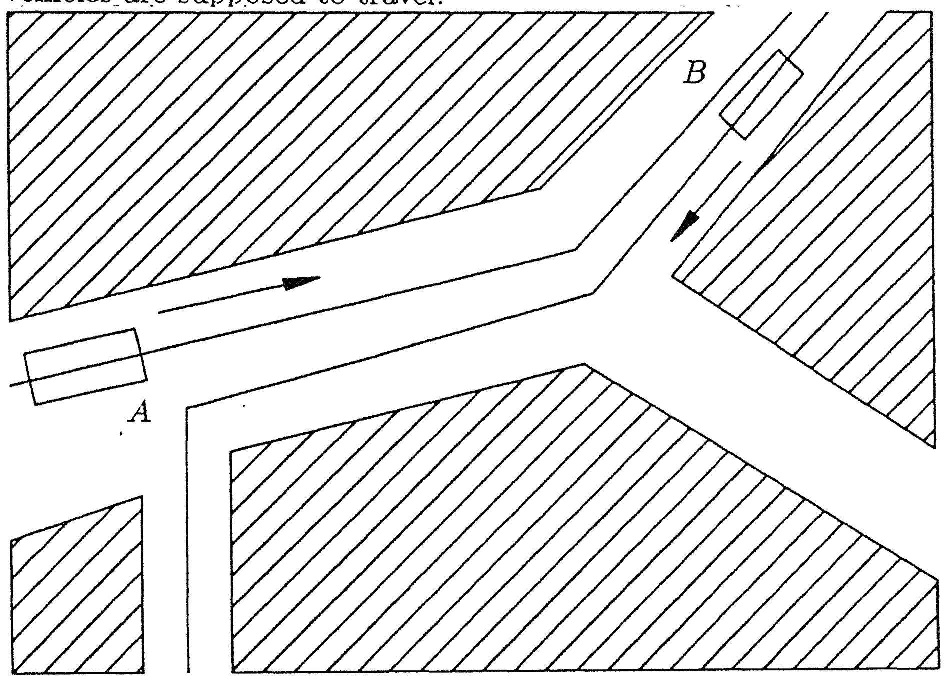


Figure 1.1: A Typical Indian Road Situation - showing road edges, vehicles and tracks.

Current models to simulate traffic flow function on one of the following aspects:

(1) Car following: Here all the vehicles are considered to be travelling in the same direction and behaviour models are being used in this regard [23]. This scheme is based upon one-dimensional approximation and ignores road width and other variations.

(2)Lateral Deviation of vehicle caused by an obstacle: It models the driver's attitude to deviate laterally (when and by what extent) and steer past the obstacle on the road. The "angle estimation model" suggests that the lateral deviation occurs at some threshold distance from the obstacle depending upon the rate of change of visual angle[1] of the same at the driver's end. Alternately a behaviour based model [19] models both the influencing

[1]The angle between the direction of the vehicle's travel and the direction in which the driver sees the obstacle

distance (i.e., the distance from the obstacle when the vehicle starts deviating) and the amount of deviation as a function of the vehicle speed as well as the obstacle contour(s).

The car following model does not really deal with obstacle avoidance. The latter model deals with single obstacle and that too with a number of assumptions of uniformity. In reality, a driver when travelling in a congested road is expected to avoid collision with vehicles travelling in arbitrary directions and so these existing models of Traffic simulation are unsuitable. It is therefore felt that some of the techniques related to robot motion planning may be more appropriate in this context.

1.2 Robot Motion Planning Techniques

Microscopic modelling of traffic flow requires us to analyse the problem of individual vehicles negotiating paths, often in close proximity. This problem is similar to that of robot motion planning, and it was felt that some of the techniques from robot path planning may be useful in analysing this problem. For example, consider the situation in Figure 1.1, where vehicle A is travelling towards the right, encounters vehicle B travelling in the opposite direction. This problem is the same as that arising in robot obstacle avoidance when a robot A which has a "goal" to the right, needs to"avoid" robot B which has a "goal" in the opposite direction. As far as a vehicle is concerned, all objects on the streets, including other vehicles, are merely things not to be collided into while trying to move in the preferred goal direction.

1.2.1 The basic path planning problem

The basic motion planning problem of robotics is defined in [17] as :

Let, $\mathcal{A}$ be a single rigid object - the robot - moving in an Eucledean Space $\mathcal{W}$,

called workspace represented as R^N with $N = 2$ or 3.
Let, $\mathcal{B}_1, \mathcal{B}_2, \ldots, \mathcal{B}_n$ be rigid objects distributed in $\mathcal{W}$ and are called obstacles.
Assuming the geometries of $\mathcal{A}$ and $\mathcal{B}_i$'s to be clearly known and so also the kinematics of $\mathcal{A}$,
The problem is : *Given an initial position (S) and a goal position (G) of $\mathcal{A}$ in $\mathcal{W}$, generate a path τ specifying a continuous sequence of position and orientation of $\mathcal{A}$ avoiding contact with $\mathcal{B}_i$'s starting at S and terminating at G. Report failure if no such path exist.*
To add complexity, we can further assume the presence of moving obstacles $\mathcal{M}_1, \mathcal{M}_2, \ldots, \mathcal{M}_m$ which move according to a predefined motion-history. The objective of $\mathcal{A}$ is now to avoid collision with both the $\mathcal{M}_i$'s and $\mathcal{B}_i$'s to find its path τ.

Furthermore, the goal may be a single configuration or a set of configurations or even a zone. There may also be a temporal constraint - that the goal has to be reached in a certain time.

In the two vehicle problem handled here, there is one moving obstacle (the other vehicle), the goal is specified as a position (without orientation) and there are no temporal constraints. Also constraints related to kinematics and dynamics based upon vehicle characteristics are imposed. Moreover the future trajectory of the moving obstacle is not known, but may be modelled by the driver according to his/her belief about the other vehicle.

1.2.2 Configuration Space Formulation

For a 2-dimensional workspace $\mathcal{W}$ the configuration of the robot $\mathcal{A}$ is described as the position and orientation of the local frame ($\mathcal{F}_\mathcal{A}$) of $\mathcal{A}$ w.r.t. the workspace frame $\mathcal{F}_\mathcal{W}$. In general, the configuration $(q_1, q_2, \ldots .q_n)$ may be written as the vector $\vec{q}$.

Configuration Space

The Configuration Space is the space of all configurations of a robot $\mathcal{A}$. Obstacles in this space are mapped as a set of all $\vec{q}$s which result in a collision. This mapping transforms the problem of planning the motion of a dimensioned object into the problem of planning the motion of a point. It makes the constraints on the motion of the robot more explicit.

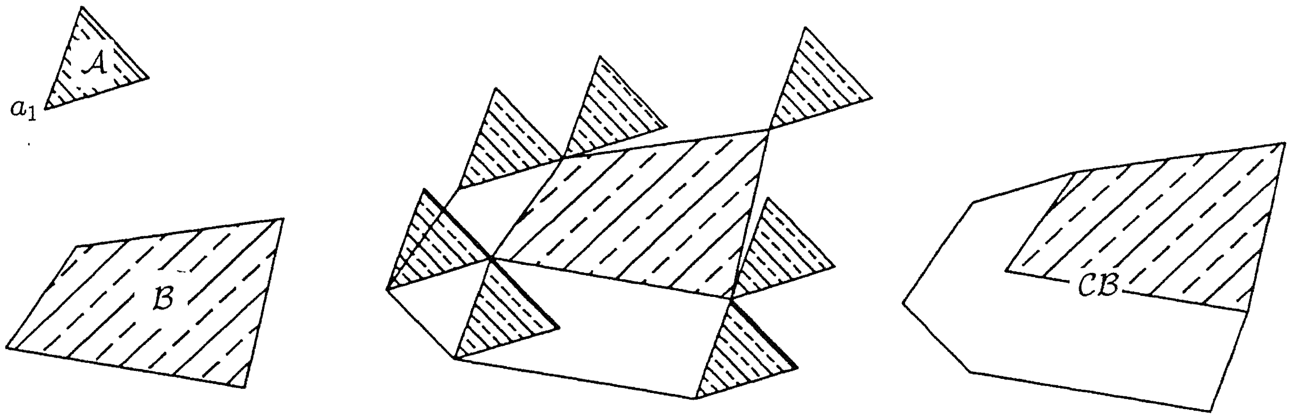


Figure 1.2: Configuration Space for Robot $\mathcal{A}$ in $\mathcal{W}$.

If we allow only translation, then taking the vertex a_1 of $\mathcal{A}$ as origin of its local frame $\mathcal{F}_{\mathcal{A}}$ reference, we can map the obstacle $\mathcal{B}_i$ to $C\mathcal{B}_i$ which is known as the C-Space of $\mathcal{B}_i$ w.r.t. a_1 of $\mathcal{A}$. For path planning purposes we can thereby reduce the robot $\mathcal{A}$ to the point a_1 and accordingly grow the obstacle $\mathcal{B}_i$ to $C\mathcal{B}_i$. The C-Space described thus is a 2-dimensional (x, y) slice for a fixed orientation of $\mathcal{A}$.

Every obstacle $\mathcal{B}_i, i = 1$ to n in the workspace $\mathcal{W}$ maps in $\mathcal{C}$ (Configuration Space) to a region

$$C\mathcal{B}_i = \left\{\vec{q} \in \mathcal{C} \;/\; \mathcal{A}(\vec{q}) \bigcap \mathcal{B}_i \neq 0\right\}$$

where, $\vec{q}$ is the configuration of $\mathcal{A}$:

$\mathcal{CB}_i$ is the C-Obstacle and $\bigcup_{i=1}^{n} \mathcal{CB}_i$ is the C-Obstacle Region.

Thus,

$$\mathcal{C}_{free} = \mathcal{C} - \bigcup_{i=1}^{n} \mathcal{CB}_i = \left\{ \vec{q} \in \mathcal{C} \ / \ \mathcal{A}(\vec{q}) \bigcap \left(\bigcup_{i=1}^{n} \mathcal{B}_i \right) = 0 \right\}$$

is the free space and any configuration in $\mathcal{C}_{free}$ is called a free configuration. Thus, a free path τ is as τ:$[0,1] \rightarrow \mathcal{C}_{free}$ with $\tau(0) = \vec{q}_{start}$ and $\tau(1) = \vec{q}_{goal}$.

Schemes for determining the Configuration Space

For convex polygons, the configuration space for translational motion can be geometrically determined by the Minkowsky sum of the concerned polygons ($\mathcal{A}$ and each of the $\mathcal{B}_i$'s at a time for each $\mathcal{CB}_i$) to give the convex polygonal C-Obstacles. In this work, the vehicle shape is assumed to be convex, which is often a reasonable approximation for cars, trucks, buses etc.

An efficient algorithm [16] constructs $\mathcal{CB}_{\theta_0}$ i.e., the θ_0 slice and maps for different θ to construct the full 3-dimensional C-Obstacle. The algorithm in brief is as:

1. Let us consider the edge vectors $\vec{e}_i^{\mathcal{A}}$ for the robot $\mathcal{A}$ and $\vec{e}_j^{\mathcal{B}}$ for each of the obstacle $\mathcal{B}$ in counter-clockwise order, where $i = 1, \ldots, n_{\mathcal{A}}$, $j = 1, \ldots, n_{\mathcal{B}}$, $n_{\mathcal{A}}$ = number of vertices in $\mathcal{A}$ and $n_{\mathcal{B}}$ = number of vertices in $\mathcal{B}$.
2. Make a combined list of -$\vec{e}_i^{\mathcal{A}}$'s and $\vec{e}_j^{\mathcal{B}}$'s.
3. Sort this list as per the direction of the edge vectors in counter-clockwise order.
4. Reconstruct the C-Obstacle polygon by taking one vector at a time sequentially from the list. This gives a single (x, y) slice for θ_0.

1.2.3 Motion Planning - Potential Field Schemes

There are many methods for solving the motion planning problem. Some of these are cell decomposition, roadmap, potential fields etc. The potential field theory

is historically originated in Coulomb's Law of Electrostatics, which defines the electric field (E) at a point, X as the work done to bring a unit charge from infinity to X under the influence of charge Q :

$$E = K.\frac{Q}{dist(Q,X)}$$

where, K is a constant of proportionality.
The gradient of this field represent the force acting on this unit charge.

In robot motion planning, the robot, represented as a point in Configuration Space is a particle under the influence of an artificial potential field U whose local variations are expected to reflect the "structure" of the free space ([17],[4],[12]). The potential function is defined over the free space as the sum of an attractive potential pulling the robot towards the goal configuration and repulsive potential(s) pushing the robot away from the obstacle(s). Potential functions are quasi-infinite inside the obstacle and are zero at some threshold distance beyond which it has no effect. At each configuration the artificial force $\vec{F}(q) = -\vec{\nabla}U(q)$ induced by the potential function is considered to act on it.

The advantage of this model is that all decisions are local and that no prior information on obstacles is needed. Information is sensed and processed in real time. The paths generated are smooth, and maintain a balanced distance from obstacles. This is in contrast to other methods for path planning where paths are straight line segments with sharp changes at the junctions. Also, the nature of different obstacles (e.g., a truck vs. a bullock cart) can be conveniently represented by changing the latency and thresholds of their potential fields. In motor tasks good correlation has been observed between biological motion planning and the potential field approach [3]. This provides further validity to the use of potential fields in emulating human drivers' behaviour.

Note that the policy of moving along the negative gradient is equivalent to the technique of steepest descent search which can suffer from local minima. During the iterations it may happen that the robot has gone inside a "well" from which

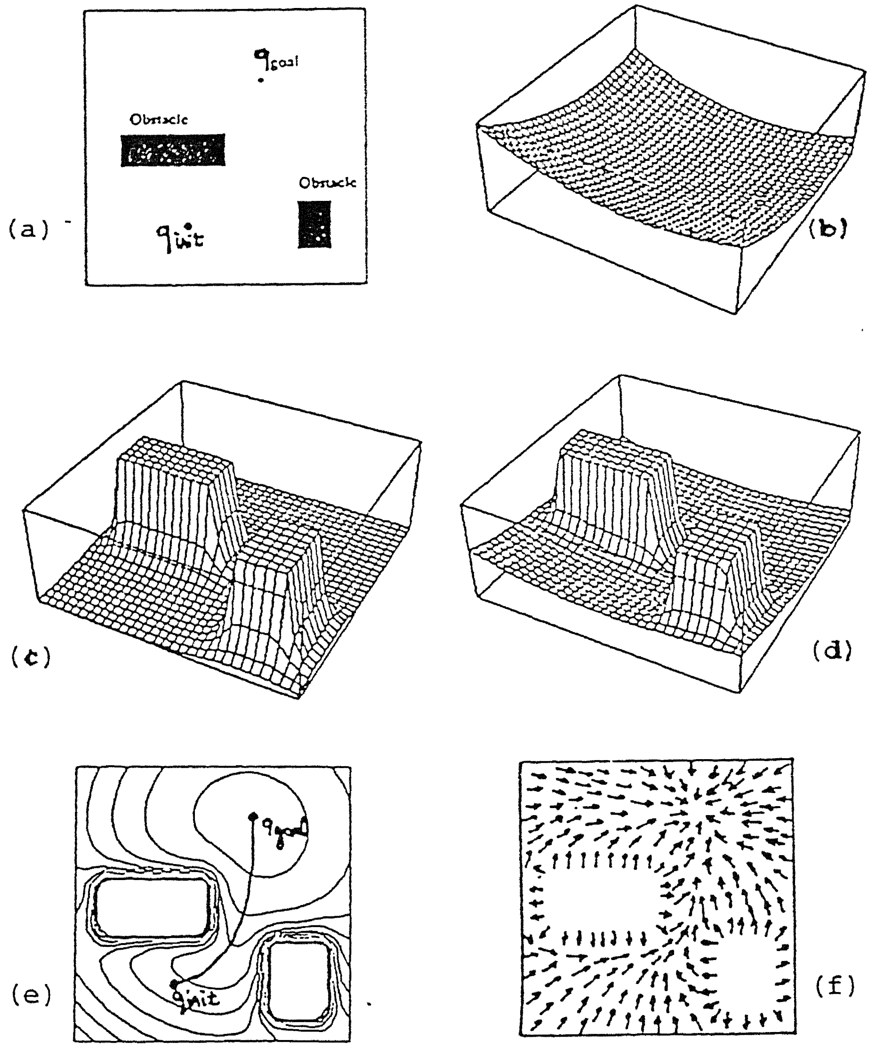


Figure 1.3: Illustration of Potential Field in a given workspace $\mathcal{W}$.

A simple 2-dimensional configuration space with two polygonal C-Obstacles is depicted in (a). (b) shows an attractive potential field generated by the goal configuration q_{goal}. (c) shows the repulsive potential generated by the C-Obstacles. (d) shows the sum of the two potentials. (e) displays the equipotential contours of the net potential and a path obtained by following the gradient whose orientations are shown in (f).

[Figure taken from Robot Motion Planning by J.C.Latombe - Fig. 8., Page 20]

the potential increases in all directions yet it is not the goal. Some ad hoc methods are sometimes used to come out of such local minima zone:

(a) Modify potential function : Strategies like oval potentials [22], multiple potential field [18], hybrid potential field [24] claim to reduce the local minima.

(b) Drop an artificial obstacle at the local minima to exit the well.

The potential function commonly used in Robotic Path Planning are taken to be positive for the obstacles (repulsive in nature) and negative for the goal (attractive in nature). The common form of expression for such force (gradient of the field) is :

$$\vec{F} = \left|\frac{k}{r^n}\right| \hat{r}$$

where r is a measure of distance from the robot to the obstacle/goal. k is a positive real constant and n is a positive integer which determines how rapidly the potential changes as the robot moves towards the obstacle/goal. Usually n is higher for obstacles such that the repulsive potential increases sharply as the robot moves closer and at some threshold distance of separation, the effect of the obstacle is nil. k for goal is assigned a higher value than k for obstacles to drag the vehicle towards the goal. For obstacles, higher the value of k, higher is the repulsive field and safer is the navigation.

1.2.4 Multiple Moving Obstacles

When motion is planned for more than one robot having independent start and goal in the same workspace, separate C-Spaces are needed to be computed dynamically for each of the robots. Here also different path planning techniques like roadmap, cell decomposition and potential field techniques can be applied.

Erdmann and Lozanzo-Pérez suggest "Decoupled" strategy in which independent paths for all the moving objects are prioritised to take care of conflicts. Fujimura [8] uses octrees to discretise and search the workspace. Kamal Kant

& Zucker [14] developed an approach by combining static motion planning to overcome fixed obstacles and then planning the velocity along the path to avoid collision with moving ones. A different approach to local path planning "Divergent Stereo" uses the visual motion field for navigating long corridors ([25],[5]). Barraquand, Langlois and Latombe [2] describe a simple potential field based model for planning the motion in a narrow corridor where the robots often backtrack to overcome local minima. Holenstein and Badreddin [9] considered the effect of velocity in their behaviour based model using repulsive potential field around the robot. Howarth and Toal [10] developed a model that uses qualitative reasoning for path planning.

1.3 Nonholonomic Constraints

A nonholonomic equality constraint arises when the velocity history is needed to obtain the current position represented as a non-integrable equation involving the configuration parameters (x, y, θ) and their derivatives. Such a constraint do not reduce the dimension of $\mathcal{A}$'s configuration space but reduces the dimension of the space of the velocity directions.

Let us consider a car-like robot $\mathcal{A}$ at configuration $\vec{q} = (x, y, \theta)$. Due to kinematic constraints $\mathcal{A}$ can only move in a finite angular zone forward or backward. The instantaneous motion of $\mathcal{A}$ is determined by two parameters : the linear velocity along its main axis and the steering angle. When both linear velocity (v) and steering angle (ϕ) are non-zero, $\mathcal{A}$ changes both its position and orientation i.e., the configuration space remains 3-dimensional (see section 2.1).

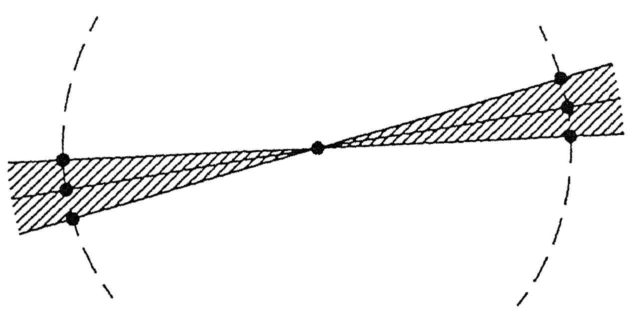
From the initial configuration of $\vec{q}$ at time t, the next desirable configuration $\vec{q}'$ at time $t + \Delta t$ will be a function of $\vec{q}$.

As per the model suggested by Latombe [17], for a car like robot $\mathcal{A}$ (a model physically quite close to our model) at a given configuration $\vec{q}$, the nonholonomic path planner generate at most six successors of $\vec{q}$ by setting two control parameters

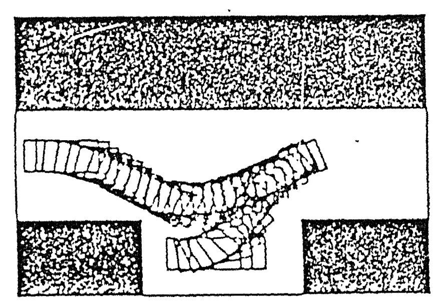
- velocity v and steering angle ϕ to the six values in:

$$\{ -v_0 \, , \, v_0 \} \times \{ -\phi_{max} \, , \, 0 \, , \, +\phi_{max} \}$$

and the path is found using A* algorithm. These possible configurations are six discrete points in a two sided cone (Figure 1.4). It uses a fixed velocity model and can switch between velocity states in a single time step. It does not consider constraints from dynamics.



(a)



(b)

Figure 1.4: Nonholonomic Path Planning

(a) Two Sided Cone Region

(b) Path found out by Latombe's Algorithm

[Figure taken from Robot Motion Planning by J.C.Latombe - Fig. 9.,Page - 434]

Different kinds of nonholonomic models are developed ([26], [21]) for different kinds of vehicles. Mirtich and Canny [20] developed a path planner where the nonholonomic robot navigates by a track ("skeleton") maximally clear from the C-Obstacles. Rather than using the Euclidean metric, a special metric called the SFP (Shortest Feasible Path Metric) is used which captures information about the nonholonomity of the robot. If the robot is at a position equidistant from different C-Obstacles surrounding it, in SFP metric the front and the rear obstacles are much closer than the side ones. The robot loosely follows the "skeleton" during

its navigation. However this model fails to ensure smooth motions particularly in narrow roads or at the road junctions. Also, it does not take into account moving obstacles.

Fraichard [6] suggests a "State-Time Space" strategy for obtaining the forbidden zones dynamically, taking into account the moving obstacles. The vehicle tries to find out its trajectory (smooth splines) in state-time space considering its kinematic and dynamic constraints. Prior knowledge of other vehicle's motion is needed.

Fraichard and Laugier [7] in an important work plan and control the motion in a dynamic roadway like environment. The motion controller has two main components - the "pilot" which operates on behavioural rules, handle conflicts of motion and analyses the road situation dynamically while the "executor" generates the motion commands using potential field strategies.
Three different potential functions are combined linearly : for static obstacles, for dynamic obstacles (used only when collisions are likely) and a velocity potential that adjusts to the time constraints of the motion.
The output presented show satisfactory results with a number of vehicles travelling in different directions in different road segments. It supports features like collision avoidance of approaching vehicles, overtaking and turning.
The kinematic model is exactly the same as developed by Latombe [17]. Also, this model is weak in designing the vehicle dynamics.

Brief Overview of the new model

The model developed in the current thesis deals with a pair of vehicles moving in arbitrary directions in roads of varying width. It constructs 3-dimensional C-Space (including orientations) from a given road layout. It models the vehicle with nonholonomic constraints and imposes the effect of dynamics on the vehicle kinematics. The navigation is based on potential field schemes with minimum occurrence of local minima due to the effect of the moving obstacle(s). It provides

a preliminary basis for modelling driver behaviour during different kinds of vehicle-vehicle interaction. The simulated results shown in Chapter 3 intuitively matches a physical road situation. However, everything done was concentrated towards the solution of a two vehicle problem and multi-car (more than two cars) interactions has been intentionally avoided.

Chapter 2

Modelling the System

2.1 Vehicle Model

The vehicles are assumed to be four wheeled with steering at the front wheels. The vehicle is modeled as a convex polygon $\mathcal{A}$ moving in the workspace $\mathcal{W}$. The midpoint of the front axle is marked F and the midpoint of the rear axle is R (see Figure 2.1).Its configuration is represented as (x, y, θ) where x,y are the coordinates of R and θ is the angle between the vehicle axis RF and the global frame x axis. The vehicle geometry is specified in a local coordinate frame, $\mathcal{F}_{\mathcal{A}}$ whose origin is at R. The steering angle ϕ is the angle between the velocity at F and the axis RF. The instantaneous radius of curvature is $L/\tan\phi$ where L is the wheelbase or distance between F and R. When the vehicle moves, the point R describes a curve that must be tangent to the main axis of the vehicle, thus generating a nonholonomic constraint of the form :

$$-\dot{x}.\sin\theta + \dot{y}.\cos\theta = 0$$

If a desired direction of motion is not attainable due to steering limitations, the vehicle steers as close as possible to it.

This model is similar that of Latombe [17] with some added dynamic con-

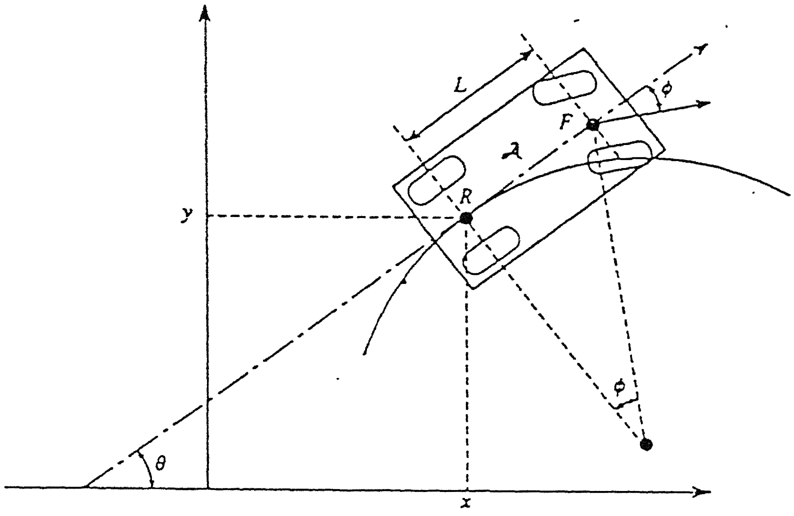


Figure 2.1: The Vehicle Geometry

straints on the maximum speed, acceleration and retardation limits depending upon engine capacity, braking power etc. For example the maximum steering angle in our case is a function of the velocity.

2.2 Potential Field Model

The model considers driver behaviour and all considerations of the near future are projected into the current instant. Since global search is not used, a potential field based approach that returns instantaneous decisions is preferable.

The problems in such an approach are that potential fields need to be defined carefully to handle the nonholonomic case. Also the driver behaviour is needed to be incorporated into the parameters of the potential field (see Section 2.3).

The basic potential field gradient in the current model is of the form k/r^n explained in Section 1.2.3. The strategy applied in the "Two-car Model" is to assign micromotion to one vehicle at a time alternately.

2.2.1 Normal Potential Field

The attractive force due to the goal acts along the gradient for the goal field :

$$\vec{F}_{att} = \vec{\nabla} U_{att} = -\left[\frac{k_{goal}}{r_{goal}^2}\right] \hat{r}_{goal}$$

where, $\hat{r}_{goal}$ is the vector from the goal to the current position and k_{goal} is a constant. However to avoid very very high fields near the goal ($r_{goal} \to 0$), we use a constant magnitude $\vec{F}_{att}$ along with the track direction. This depends on driver behaviour aspects (Section 2.2.3 and Section 2.3).

The field gradient for the fixed obstacles (e.g., road edges) is computed as:

$$\vec{F}_{rep_i} = \vec{\nabla} U_{rep_i} = \frac{k_{road}}{r_{road_i}^3} \hat{r}_{road_i}$$

where,$\hat{r}_{road_i}$ is the vector from the obstacle i to the current position and k_{road} is a constant that varies from driver to driver to reflect his/her nominal position in the lane width.

When the vehicle is in motion in a particular road segment the road potentials acting on it is essentially from the two sides (left and right) perpendicular to the vehicle motion. Varying these potentials i.e., assigning a higher value for the k_{road} from the left edge than from the right one, appropriate driving norm, e.g., left hand drive can be achieved.

Moving obstacle is that vehicle which is not served currently. When the moving obstacle is at a distance more than some critical value (depending upon the driver characteristics as discussed in Section 2.3) a potential function similar to that for static obstacles is used:

$$\vec{F}_{rep_m} = \vec{\nabla} U_{rep_m} = \frac{k_{car}}{r_{car_{other}}^3} \hat{r}_{car_{other}}$$

where,$\hat{r}_{car_{other}}$ is the distance vector from the other vehicle to the current position and k_{car} is a constant (index m indicate moving obstacle).

However, if $r_{car_{other}}$ is less than the critical value, F_{rep_m} is computed using "look-ahead" as discussed in the Section 2.2.3. Thus, the net force acting on the vehicle

is as:

$$\vec{F}_{net} = \vec{F}_{att} + \sum \vec{F}_{rep} + \vec{F}_{rep_m}$$

Latombe [17] uses an exhaustive search scheme (see Figure 1.4) to determine paths to the goal. In the current work, such a strategy is not feasible, since not only is the next position and direction of travel to be determined but also the velocity. If velocity is also a part of the vehicle state space, either the motion would have been jerky (velocity search space is too discretised) or to avoid this the search space would be infinitely large. Instead, the current work avoids search altogether and all the decisions are based on local conditions using the potential field along with vehicle kinematics, dynamics and drivers' belief about the behaviour of his/her own vehicle as well as of the other vehicles on the road.

2.2.2 Anomalous Behaviour using Potential Fields

Consider vehicles V_1 and V_2 are coming straight towards each other (Figure 2.2), with some overlapping zone between their motion paths. For the purpose of this section, we assume the vehicles are rectangles, with corners NE, NW, SW and SE.

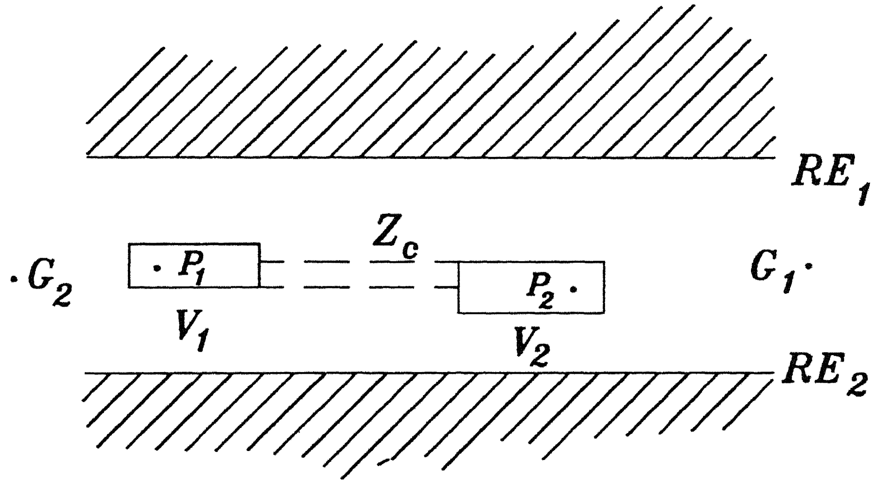


Figure 2.2: A Typical Road Scenario where there is possibility of an anomalous situation to occur.

The current positions of V_1 and V_2 are P_1 and P_2 while the current goals are G_1 and G_2 respectively. The geometry of the vehicles is defined by its vertices in its local frame, using homogeneous coordinates e.g., V_1 is defined in local frame C_{1L} as,

$$C_{1L} = \begin{bmatrix} l_1/2 & -l_1/2 & -l_1/2 & l_1/2 \\ w_1/2 & w_1/2 & -w_1/2 & -w_1/2 \\ 1 & 1 & 1 & 1 \end{bmatrix} = \{NE_1, NW_1, SW_1, SE_1\}$$

where, l_1 is the length of V_1 and w_1 is its width. At some configuration (a_1, b_1, θ_1) of V_1 its frame is given by the transformation $\mathbf{T}_1$:

$$\mathbf{T}_1 = \begin{bmatrix} \cos\theta_1 & -\sin\theta_1 & a_1 \\ \sin\theta_1 & \cos\theta_1 & b_1 \\ 0 & 0 & 1 \end{bmatrix}$$

In this situation, two kinds of anomalous motion occur when the vehicles are close :

1. One vehicle is found to turn towards the other one.

2. One vehicle starts backing up even if there is sufficient room for it to steer and travel past the other.

The reason behind this behaviour is the occurrence of local minima zone between the vehicles.

Turning towards the other vehicle

If V_2 is currently at configuration q_2, it may either continue straight and reach q_2' or it may turn *towards* V_1 and reach q_2''. In certain circumstances the latter motion may be feasible - when,

$$distance(q_1.Front, q_2'.Front) > distance(q_1.Front, q_2''.Front)$$

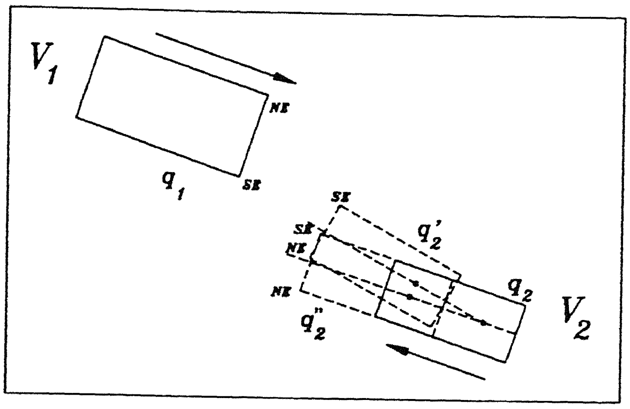


Figure 2.3: Anomalous Turning of a vehicle

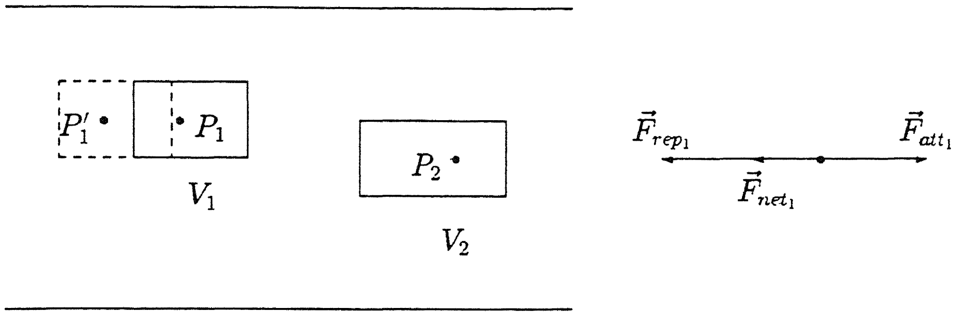
This occurs only if V_1 is in a set of special positions w.r.t. V_2 such that the above relation becomes true.

Backing up when there is free space

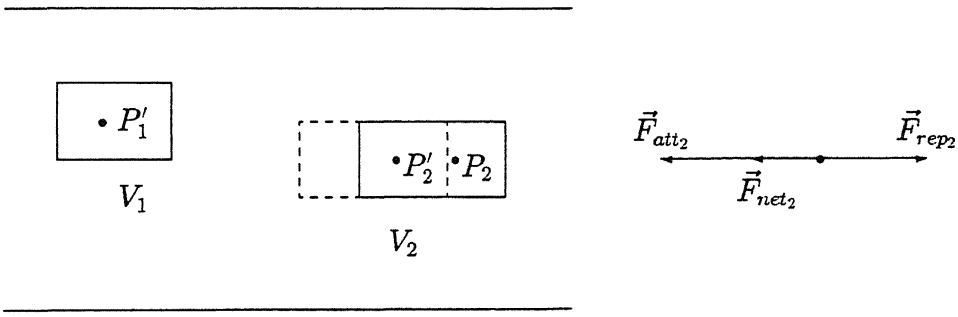
When there is a width overlap between the vehicles ,the zone marked Z_c in Figure 2.2, there may develop a local minima inside this zone. If the road edge potentials from either side are balanced, then only the forces acting on the cars are from the other vehicle (repulsive) and from the goal (attractive). Now if both the vehicles are aligned towards the goal, these forces are in exactly opposite directions. Beyond some threshold distance between the vehicles, the repulsive force may compel the vehicle to backup. If one vehicle backs up, the distance between the vehicles increase, causing the other to move forward. Thus the local minima zone shifts between the vehicles once again and the anomalous behaviour continues. This is shown in Figure 2.4.

2.2.3 Look-ahead Consideration - Projective Technique

As seen in the previous section, two kinds of anomalous behaviours are observed during vehicle-vehicle interactions. These are caused by local minima in the zone ahead of the drivers. In reality, a driver avoids such minima by incorporating



(a) i th. iteration.



(b) $(i+1)$ th. iteration.

Figure 2.4: Backing up of a vehicle

his/her belief of future events, obtained as projections from the current state onto the future. A simple projective model is developed here to reflect this as a "shadow" on the field.

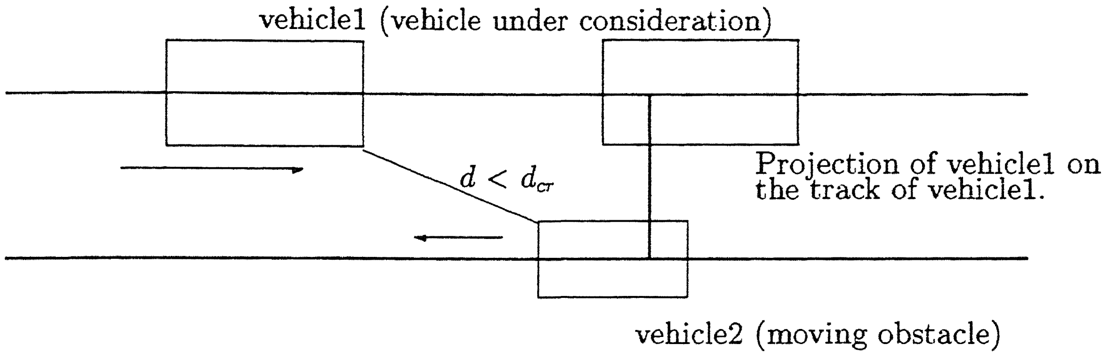


Figure 2.5: The Projective Technique

This projected shadow (see Figure 2.5) along with the relative velocity of travel create a repulsive effect on vehicle1 (the vehicle under consideration) enabling it to take a turn beforehand and thus avoid reaching a probable local minima zone. When vehicle1 locates vehicle2 at distance d_{cr} depending upon its own characteristics (aggressiveness), the driver projects his/her belief of the vehicle's motion and also that of the other vehicle to obtain the "shadow" of vehicle1 in advance onto its own track. This "shadow" generates an additional field enabling him/her to decide about deviating from his original track.

The projected shadow is taken into consideration only when d is less than some critical distance (d_{cr}) and relative velocity is positive (details in Section 2.3). The repulsive force ($\vec{F}_{rep_m}$) is given by:

$$\vec{F}_{rep_m} = k_{shadow}.\frac{E_{shadow}}{r^3_{car_{other}}}\hat{r}_{car_{other}}$$

where, E_{shadow} is computed depending on driver characteristics and his/her belief

about the other vehicles as in Section 2.3.

k_{shadow} and $\hat{r}_{car_{other}}$ depend on the relative location of the shadow w.r.t. the other vehicle. If these do not intersect, $k_{shadow} = k_{shadow\_non\_penetrate}$ and $\hat{r}_{car_{other}}$ is along d. Otherwise, $k_{shadow} = k_{shadow\_penetrate}$ and $\hat{r}_{car_{other}}$ is along the vector from R (i.e., midpoint of the rear axle) of the other car to the R of the shadow.

$k_{shadow\_penetrate}$ is assigned a much higher value ($\times$ 100) than $k_{shadow\_non\_penetrate}$.

This "shadow" is constructed as the projection of the vehicle's own physical configuration located at the foot of the perpendicular to the track of vehicle1 from the current position of vehicle2. This scheme shows satisfactory results even when the vehicles are moving in same direction. However, no psychological validity is claimed for this model, a function that of driver's belief. In reality the driver continually senses the other vehicles for situations when others do not act according to the belief.

2.2.4 The Dynamics of the Vehicle

One of the main differences of the current work from earlier models is the incorporation of dynamic consideration, e.g., computing velocity dependent maximum steering angle. The dynamics of the vehicle also affects its maximum acceleration and deceleration rates. It becomes particularly relevant at turns.

Let the C.G. of the vehicle be at a height of h from the ground. The mass of the vehicle is m and the size is $l \times w$. The overturning torque can be computed as

$$T = \frac{mgw}{2h}$$

The maximum steering angle is computed based upon the radius of curvature $R = \frac{L}{\tan\phi}$ where, ϕ is the steering angle and L = Distance between the front and the rear axles (see Section 2.1). The radial centrifugal force is $\frac{v^2}{R}$ (where v is the velocity of the vehicle) which must be less than the overturning torque. Hence,

$$\phi \leq \tan^{-1}\left[\frac{Lgw}{2hv^2}\right]$$

In practice, the actual steering angle is determined from the net field acting on it, resulting a velocity change of dv. This is added to the current velocity v to obtain to obtain the new direction of motion, within the constraints of the maximum steering angle.

2.3 Modelling the Driver Behaviour

One of the major objectives of the current work is to formulate the potential field in terms of driver behaviour characteristics. The current model however is extremely rudimentary using several scalar characteristics such as aggressiveness, stay-on-your-side-of-the road, other-car-influence etc., as well as some very simple belief functions. The action of each vehicle and its driver is based on the current situation and its own belief regarding other agents' behaviour and this is reflected in its own parameter set. This mechanism is stimulus-response type in nature.

Driver Aggressiveness

The driver aggressiveness criteria is typically represented as an index (μ) in a scale of 1-100. A more aggressive driver is assigned with a higher value of μ e.g., an extremely rash driver has μ = 90-100 whereas a moderately safe driver has it in the range of 40-60. This value is also dependent on the type of the vehicle; e.g., in the Indian context truck drivers are considered most aggressive followed by the bus, car and the rickshaw driver. In this model, aggressiveness has no independent effect on the velocity with which the vehicle is travelling. It plays a key role when the vehicle has to yield to other vehicles, while taking turns or while braking. For example, When distance d between the two vehicles is less than some critical value (d_{cr}), the projective potential field (Section 2.2.3) is applied. d_{cr} is a rapidly decreasing function of μ in the form:

$$d_{cr} = |\vec{v}_{rel}| \cdot \left[Braking\ Time \times Safety\ Factor \times \left(1 - \frac{b}{\mu^2}\right)\right]$$

where, $\vec{v}_{rel}$ is the relative velocity of travel, *Braking Time* is a parameter related to the driver characteristics and b is a global constant. The global *Safety Factor* is thus reduced by the factor (1 - $\frac{b}{\mu^2}$). Hence, the car having a lower μ may deviate from the track earlier in order to give room for the more aggressive driver. Also the shadow potential constant (E_{shadow}) is dependent upon the aggressiveness (μ_c) of the driver, as well as $\vec{v}_{rel}$, estimated size of the approaching vehicle (S_o) and the estimated aggressiveness (μ_o) of the approaching driver:

$$E_{shadow} \propto \frac{|\vec{v}_{rel}| \,.B(S_o)}{\mu_c.B(\mu_o)}$$

where, index $B(\ )$ indicate the output from the Belief function. This E_{shadow} is further modulated by *k_shadow* (Section 2.2.3).

The aggressiveness index (μ) is also used while the vehicle is turning or braking. A more aggressive driver will use a shorter braking threshold (d_{th}) and the braking force (F_{br}) will be greater:

$$F_{br} \propto \mu$$

$$d_{th} \propto \frac{1}{\mu}$$

Belief functions

Currently the model has belief functions for estimating the aggressiveness of the other driver. An ad hoc multiplier has been used to estimate sizes, but no psychological validity is claimed for any of these functions. However, belief functions modulate the driver's entire knowledge of the world: the other systems as well as his own. Consider the scenario described below:

> *Let us take an example of a rickshaw puller pulling a rickshaw through a particular road segment when he senses another vehicle approaching towards him. He can only see the front of the approaching vehicle. From his experience (i.e., belief) he can identify the type of the vehicle and*

hence determine its approximate size which is used in his projective planning. He can also estimate the approaching driver's aggressiveness e.g., if that vehicle is a truck, he infers that the driver would be highly aggressive. He also has reasonable estimates about his own vehicle characteristics. Thus, he can make a decision on yielding to the other vehicle and how much deviation is needed for his own safety.

Modelling belief is an extremely complicated process. Koller [11] has constructed a "belief network" for analysing symbolic traffic flow explaining features like lane changes in a highway traffic simulation. In Indian context modelling a high level belief based system is quite relevant. As for example, consider the situation where a bus is approaching a turn, then just by reading the route number, one can estimate the likely track to be adopted by that bus. However, to predict features like this, tremendous amount of world knowledge is also required. In the current work, only a simple model has been developed.

In the current belief model , the input is velocity of the other vehicle as well as some of its physical dimensions and parameters (which the driver of the vehicle under consideration can find out almost exactly). The outputs are estimated size and aggressiveness of the other vehicle.

2.4 Modes of Travel : Normal (in Segment) Motion, Turning and Goal Reaching

Different travel modes are used due to varying effect of the goal along with the driver attitudes. A route planner decomposes the route of each vehicle into track segments and returns the track list. At the road junctions the vehicle switches from one segment to another. This mode is called Turning. At the Goal Reaching mode the vehicle travels in the last track segment and nears the final goal. The normal mode is used while travelling in a single track segment.

2.4.1 Normal (In Segment) Motion Mode

Inside the segment the effect of the goal is represented as a constant vector field to prevent unrealistic accelerations as it approaches the goal. The acceleration in this mode depends upon the field intensity and nonholonomic constraints of the vehicle. When the velocity reaches the upper limit the driver maintains the current velocity even when he is nearly approaching the goal. However, influence of other car(s) can significantly alter this velocity of travel (avoiding moving obstacles is given a higher priority).

2.4.2 Turning Mode

For the turning operation the driver has to reduce the vehicle velocity and then shift the target from the current goal to the next. The driver has prior information about the next track and can calculate approximately where he has to take a turn. Before turning he has to reduce the vehicle speed; - the point at which the brake is applied being a function of his aggressiveness. In human driving also this phenomenon occurs as at some point the driver has to shift his attention from one goal to the next. The velocity during turning is purely a function of the current potential field gradient subject to the kinematics and dynamics of the vehicle.

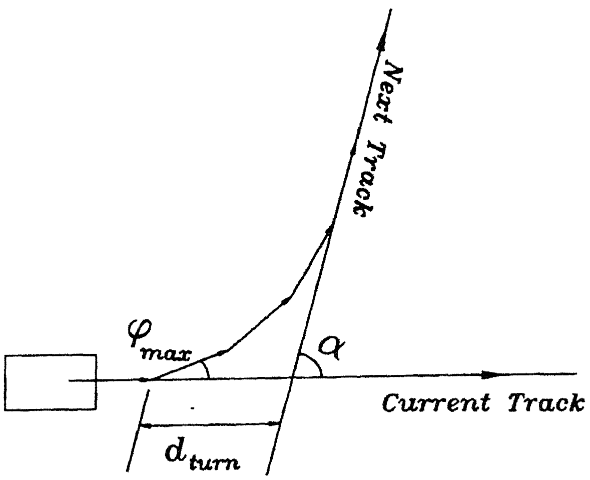


Figure 2.6: The Switching of the Goal

When a vehicle navigates, it takes an element from the track list and considers this as the current goal. At some distance before the current goal, depending upon its ability to steer, the vehicle shifts the goal to the next element from the list and continues.

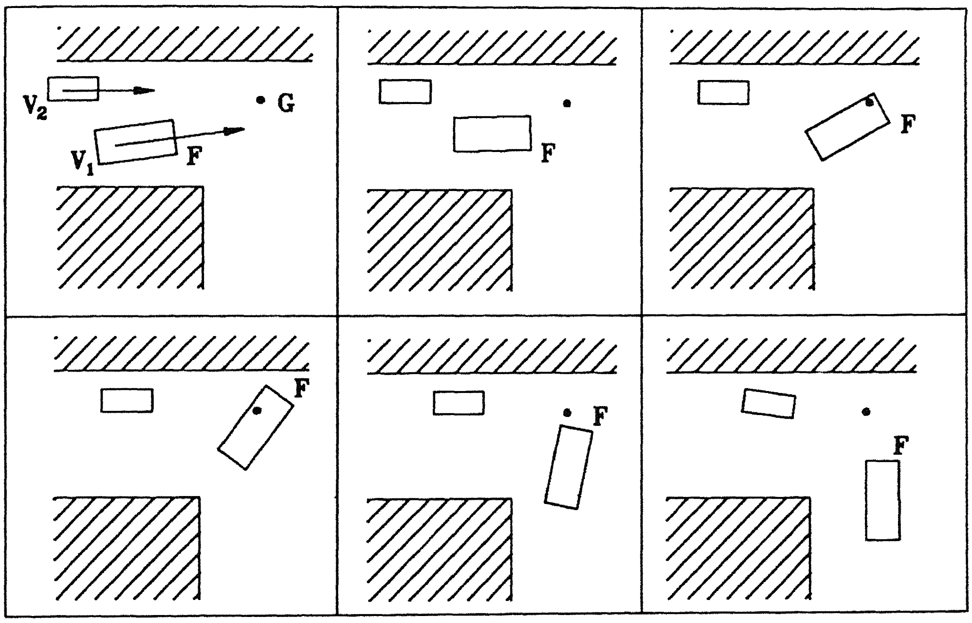


Figure 2.7: Backing up during Turning

Vehicle V_1 backs up at the road junction (The front of the vehicle is marked F). This is because V_1 has deviated from its original track by the action of V_2 right at the cross-road.

Let $\vec{v}$ be the current velocity of the vehicle under consideration and α be the angle between $\vec{v}$ and the next track segment. The threshold distance from the current goal for goal switching can be computed as:

$$d_{turn} = \frac{L.\tan(\alpha/2)}{\tan\phi}$$

The effect of discretisation into steps of length $|\vec{v}|.\Delta t$ needs to be taken into account and thus d_{turn} becomes:

$$d_{turn} = |\vec{v}|.\Delta t.\left[\sum_{i=1}^{n}\cos(i.\phi_{max}) - \cot\alpha\sum_{i=1}^{n}\sin(i.\phi_{max})\right]$$

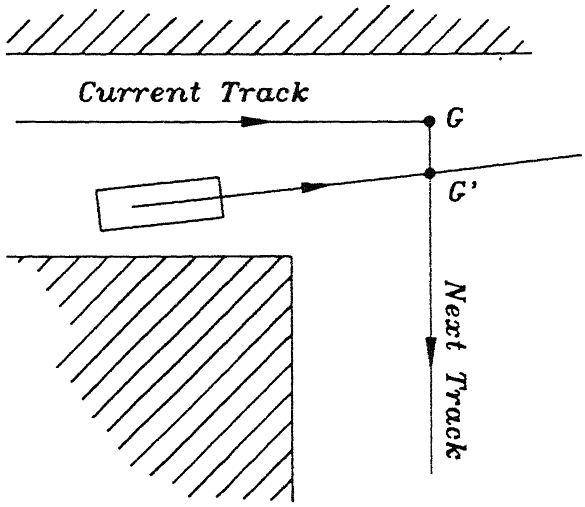


Figure 2.8: Locating the virtual goal on turning

where, ϕ_{max} = maximum steering angle attainable at velocity $\vec{v}$, $n = \lfloor \frac{\alpha}{\phi_{max}} \rfloor$ and $\alpha \neq 0°$.

Here, d_{turn} needs to be calculated along the current direction of the vehicle's travel and not along the vector to the goal. The later could have resulted in backing up at the turn (Figure 2.7). While turning, a **virtual goal** G' is used instead of the original goal G. G' is located where the current direction of the vehicle's motion intersects the next track segment (Figure 2.8).

2.4.3 Goal Reaching Mode

Deceleration before reaching the goal is necessary, otherwise the gradient near the goal is infinite and the vehicle will shoot past the goal at tremendous speed. In this mode the vehicle speed has slowed down so that it stops near about the final target. Depending upon the current velocity, goal distance and the field gradient the driver alters the velocity taking into account the vehicle's braking ability.

Chapter 3

Implementation and Results

The implementation is done in Borland C Version 2.0 on a 80486 platform using VGA graphics adapter.

3.1 Program Structure

The program consists of different modules (.C extensions) along with several input and output data files (Figure 3.1). The program MAIN.C is the main program which coordinates these different modules right from getting the input data to the output generation (on the screen as well as in different output files).

3.1.1 The Inputs

The input data is read from several files and included in the data structures:

1. The Vehicle data which includes the Driver data.
2. The Track data.
3. The Road Boundary data.

The **Vehicle data** consists of:

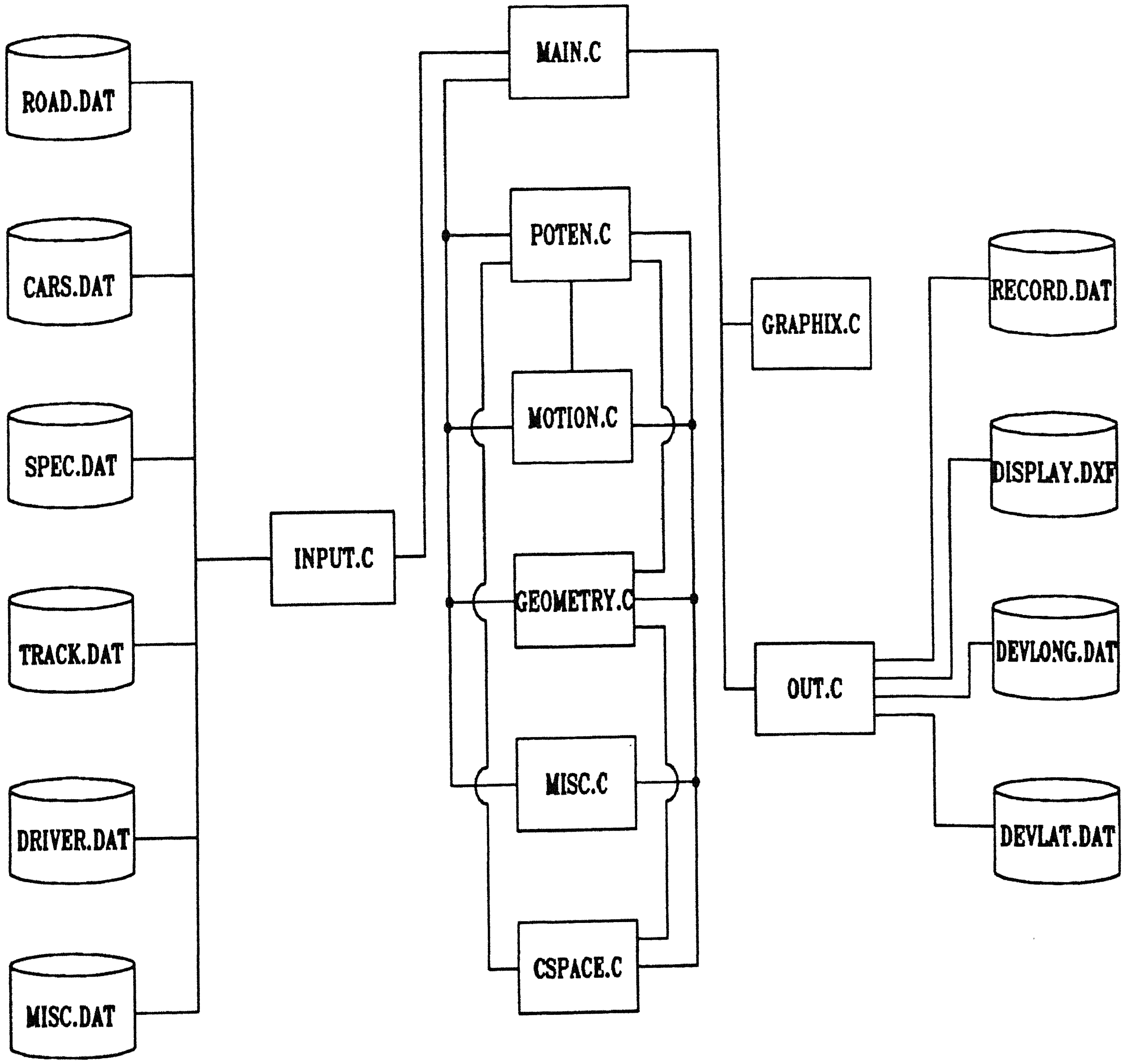


Figure 3.1: The Program Structure

1. Physical Shape i.e., configuration of the vehicle where it is modelled as a convex polygon in a local coordinate frame. This frame is placed at the midpoint of the vehicle's rear axle. This information is read from the file cars.dat and included as polygon data. Approximate vehicle size and maximum vehicle dimension are computed from these information and included in the Vehicle data structure.

2. Technical specifications such as, maximum car speed, engine power, braking power and the maximum steering angle. These are read from the file spec.dat.

3. The driver data structure contain the potential field parameters to influence the driver of the vehicle. These are as k_{goal}, k_{car}, $k_{shadow\_non\_penetrate}$, $k_{shadow\_penetrate}$, k_{road_near}, k_{road_far} etc. Also it contains the driver's Aggresiveness index (μ). This information comes from driver.dat.

4. The path information i.e., the start and the goal point (obtained from the track data structure), the current position and orientation of the vehicle in the road (x,y,θ), the current velocity of the vehicle and pointers to the track list.

The **Track data** structure holds the information about the entire track in form of vertex list of the track read from the file track.dat (the route planner). The orientation of each track is computed and included in the data structure. This information is passed to the Vehicle data structure when the vehicle switches its goal.

The **Road data** structure contain the physical configuration of the fixed obstacles i.e., the road edges in the global coordinate frame (the coordinate frame of the workspace). This is a polygonal data structure.

3.1.2 The Outputs

The output is shown in screen using Borland C Graphics Library functions. Additionally, some output files are created containing the following information:

1. Record.dat stores the entire track history through out the trajectory.
2. Devlong.dat stores the Longitudinal distance data from the trajectories which is further plotted using Grapher.
3. Devlat.dat stores the Lateral deviation data from the trajectories for each of the vehicles. This is also plotted using Grapher.
4. Display.dxf stores the trajectory in Autocad dxf format which can be retrieved by *Autocad Release* 10.

3.2 Results

In this section trial runs are presented for different situations. A list of parameters used for the simulation is presented along with the track data for each of the cars. For basic situations like vehicles approaching each other, vehicles in same direction etc., Time vs. Lateral Deviation and Time vs. Longitudinal Distance plots are produced. Also a brief analysis is done to support and explain the observation(s). (The time resolution for the outputs = 0.1 seconds.)

3.2.1 Single vehicle in motion

In this case, only one vehicle is in action. It moves on a narrow road and during the course of motion, it has to take a turn.

Parameter	Value
	vehicle A
Type of vehicle	Car
$kgoal$	7000
$kroad\_near$	300
$kroad\_far$	2400
Driver's Aggressiveness	75
Vehicle Size	4.5m × 3.0m
Engine Power	600
Brake Power	700
Maximum Speed	54 kmph
Maximum Steering Angle	5°

vehicle A	
x	y
-25	250
325	250
325	480

Table 3.1: Parameters: Single vehicle is in motion.
(a) The Vehicle and Driver Characteristics.
(b) The Path for the vehicle.(1 unit = 0.125m)

Analysis

The car is moving on a narrow road. The starting point is right at the centre of the road. Soon it moves to the left to its steady state configuration. It continues to keep to the left even after taking the turn.

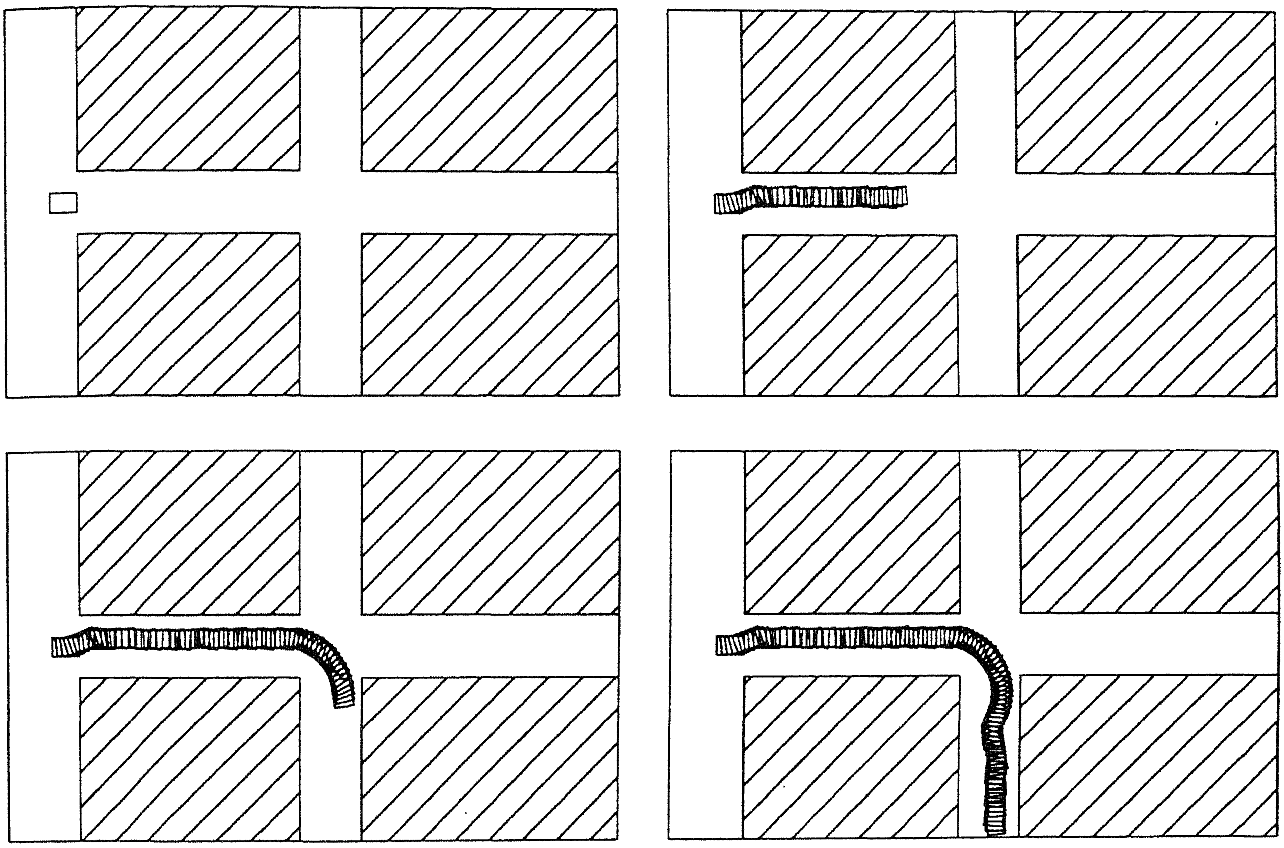


Figure 3.2: The simulation - Single Vehicle in motion.

3.2.2 Vehicles crossing - Wide road

Two cars are moving in opposite direction on a broad road. The cars approach one another, yield and move away.

Parameter	Value	
	vehicle A	vehicle B
Type of vehicle	Car	Car
kgoal	7000	7000
kroad_near	900	900
kroad_far	7200	7200
kcar	100	100
kshadow_intersect	9000	9000
kshadow_non_intersect	150	150
Driver's Aggressiveness	60	60
Vehicle Size	4.5m × 3.0m	4.5m × 3.0m
Engine Power	550	550
Brake Power	600	600
Maximum Speed	45 kmph	45 kmph
Maximum Steering Angle	5°	5°

vehicle A		vehicle B	
x	y	x	y
-210	250	700	250
650	250	225	250

Table 3.2: Parameters: Vehicles crossing - Wide road
(a) The Vehicle and Driver Characteristics.
(b) The Path for the vehicles.(1 unit = 0.125m)

Analysis

As seen in the simulation and confirmed in the plots (Figure 3.3 and Figure 3.4), at the start both the vehicles were placed right at the centre of the road. When the vehicles start moving, the non-uniform road potentials push both the cars to the left (w.r.t. it's direction of travel). When the cars cross each other they

are sufficiently apart. Yet they deviate by a small amount depending upon their current velocity and driver's aggressiveness(μ). Since both the cars have equal μ, both turn almost equivalently. Finally they take turn towards the goal, retard and stop.

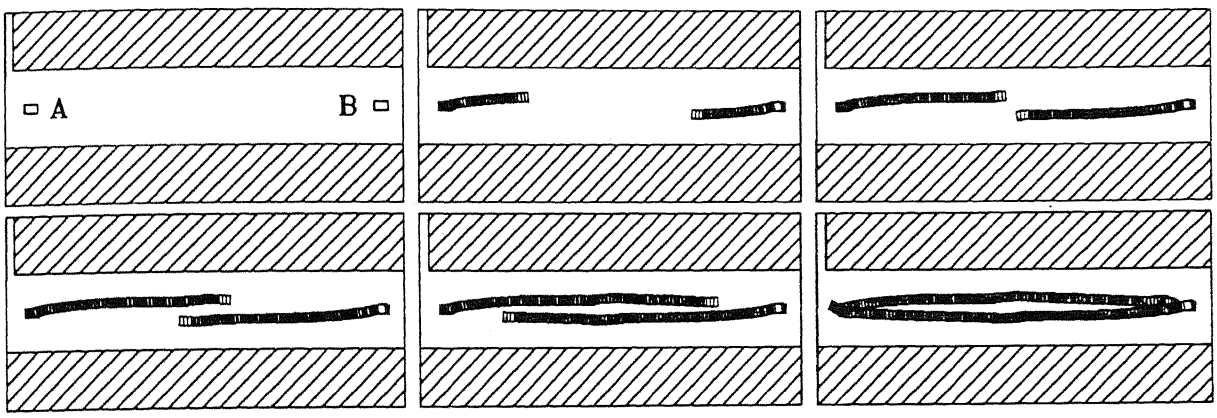


Figure 3.3: The simulation - Two vehicles in wide road

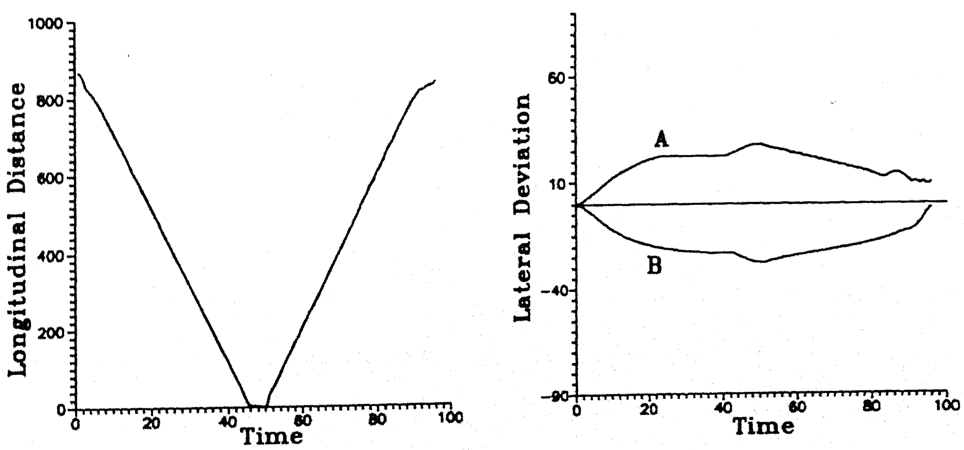


Figure 3.4: Characteristic Curves - Two vehicles in wide road

3.2.3 Vehicles crossing - Narrow road

Two cars are moving in opposite direction in a narrow road. The cars approach one another, yield and move away.

Parameter	Value	
	vehicle A	vehicle B
Type of vehicle	Car	Car
kgoal	9000	9000
kroad_near	200	200
kroad_far	1200	1200
kcar	100	100
kshadow_intersect	9000	9000
kshadow_non_intersect	150	150
Driver's Aggressiveness	60	60
Vehicle Size	4.5 × 3.0m	4.5m × 3.0m
Engine Power	550	550
Brake Power	600	600
Maximum Speed	45 kmph	45 kmph
Maximum Steering Angle	5°	5°

vehicle A		vehicle B	
x	y	x	y
110	250	600	250
628	250	50	250

Table 3.3: Parameters: Vehicles crossing - Narrow road
(a) The Vehicle and Driver Characteristics.
(b) The Path for the vehicles.(1 unit = 0.125m)

Analysis

When the cars start moving, the non-uniform road potentials push both of them to the left (depending upon it's direction of travel). But since the road is narrow, the cars cannot clear-off when they come closer. So, they deviate more in this case to avoid collision. However their deviation is again restricted by road edges. After

yielding, again they try to travel to the steady-state position i.e., keep to the left. (see Figure 3.5 and Figure 3.6).

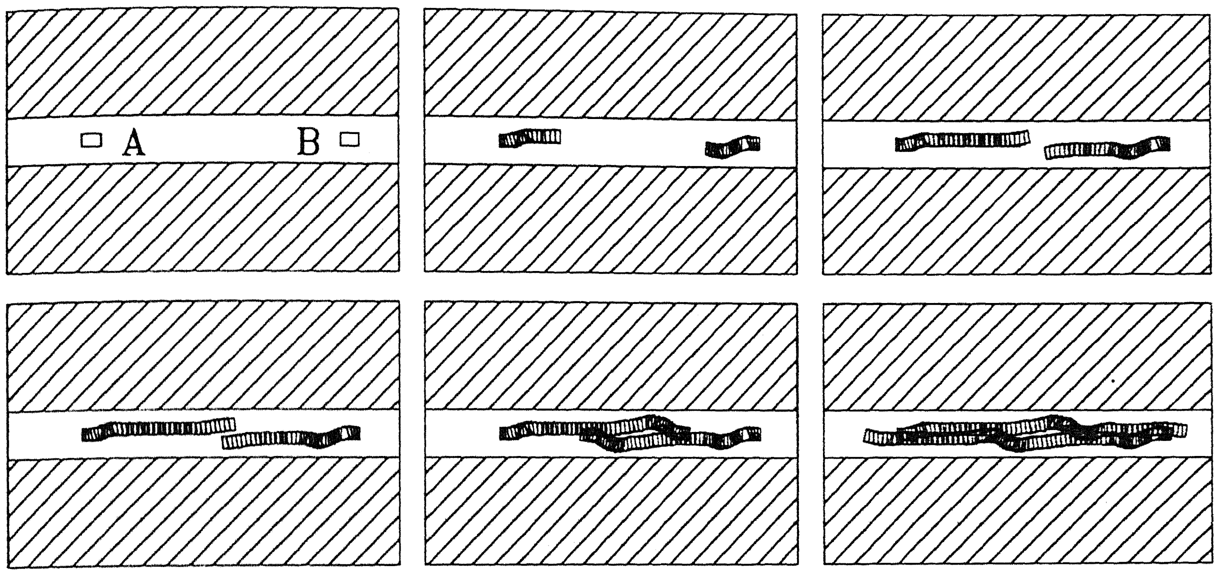


Figure 3.5: The simulation - Two vehicles in narrow road

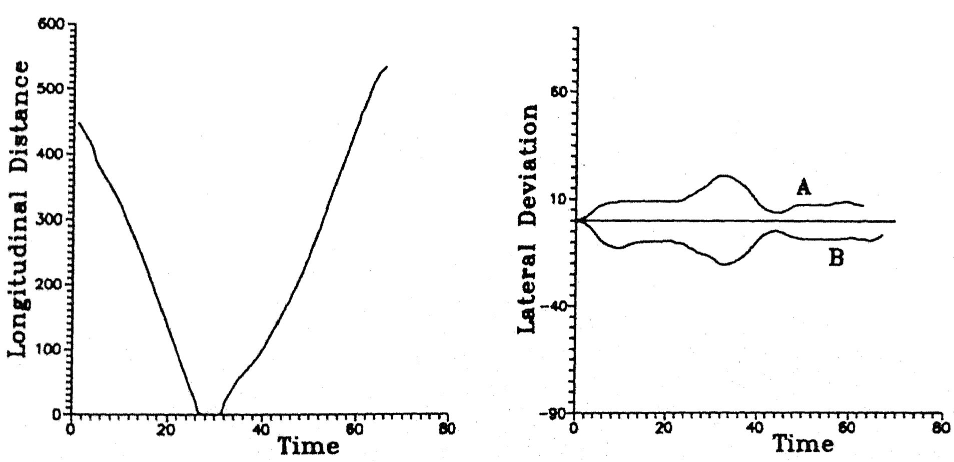


Figure 3.6: Characteristic Curves - Two vehicles in narrow road

3.2.4 Truck overtaking a Car

A car is moving on the road. A truck approaches it from behind and overtakes the car. Both vehicles continue to move on in the same direction.

Parameter	Value	
	vehicle A	vehicle B
Type of vehicle	Car	Truck
kgoal	10000	10000
kroad_near	600	200
kroad_far	2400	1600
kcar	10	10
kshadow_intersect	5000	9000
kshadow_non_intersect	150	150
Driver's Aggressiveness	60	100
Vehicle Size	4.5m × 3.0m	6.75m × 3.75m
Engine Power	550	600
Brake Power	600	700
Maximum Speed	31.5 kmph	56.25 kmph
Maximum Steering Angle	5°	5°

vehicle A		vehicle B	
x	y	x	y
-20	250	-20	255
600	250	750	255

Table 3.4: Parameters: Overtaking
(a) The Vehicle and Driver Characteristics.
(b) The Path for the vehicles.(1 unit = 0.125m)

Analysis

The car A starts ahead of the truck B and both moves to left to the steady state. B travelling with a higher velocity moves closer and at some critical distance behind, it decides to overtake. So, it starts deviating (at time = 30) After deviating to the right (between time = 30 and 50) B catches up A and moves parallely to it

(The Time vs. Longitudinal Distance curve shows this phase between time = 40 and 50) with the safer driver of A deviating to his left by a small amount. After forging ahead, B returns to its steady-state configuration at time = 65 just in front of A. The driver of A reduces his speed and further deviates to the left. Thus the Longitudinal distance increasing more steeply. After a certain safe clearance is created, A starts returning to its steady state configuration (at time = 80) At time = 90, B reaches its goal. A continues to move further and so the Time vs. Longitudinal Distance curve droops.

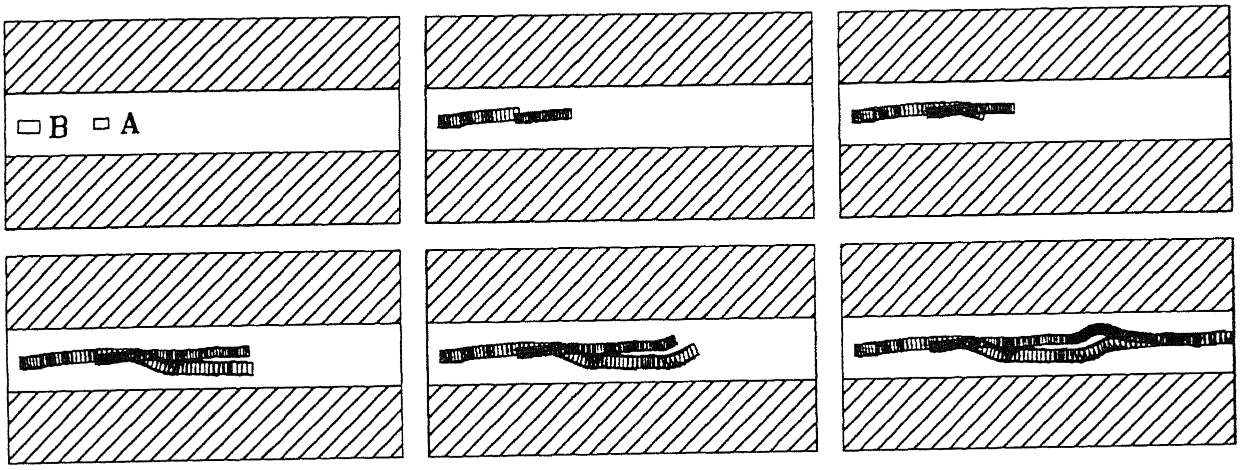


Figure 3.7: The simulation - Truck overtaking a car

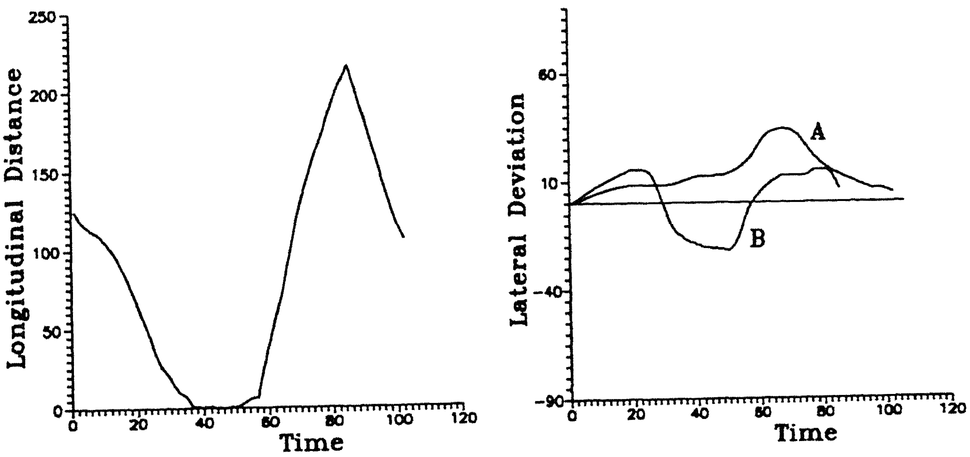


Figure 3.8: Characteristic Curves - Truck overtaking a car

3.2.5 Vehicles Crossing - Unequal Aggressiveness

A car is moving in road. A more aggressive bus approaches towards the car. Both the vehicles yield and continue to move on in their respective directions.

Parameter	Value	
	vehicle A	vehicle B
Type of vehicle	Bus	Car
kgoal	7000	7000
kroad_near	300	300
kroad_far	2400	2400
kcar	30	30
kshadow_intersect	9000	9000
kshadow_non_intersect	50	150
Driver's Aggressiveness	80	60
Vehicle Size	5.62m × 3.5m	4.5m × 3.0m
Engine Power	600	550
Brake Power	700	600
Maximum Speed	54 kmph	45 kmph
Maximum Steering Angle	5°	5°

vehicle A		vehicle B	
x	y	x	y
-80	250	700	250
725	250	-75	250

Table 3.5: Parameters: Vehicles crossing - Unequal Aggressiveness
(a) The Vehicle and Driver Characteristics.
(b) The Path for the vehicles.(1 unit = 0.125m)

Analysis

When the car(B) and the bus(A) approach each other B deviates a bit earlier since the car driver is safer (Table 3.5). However, as it was found necessary, A also deviated to prevent collision. As seen in Figure 3.9 and Figure 3.10, the deviation of A is much less compared to that of B.

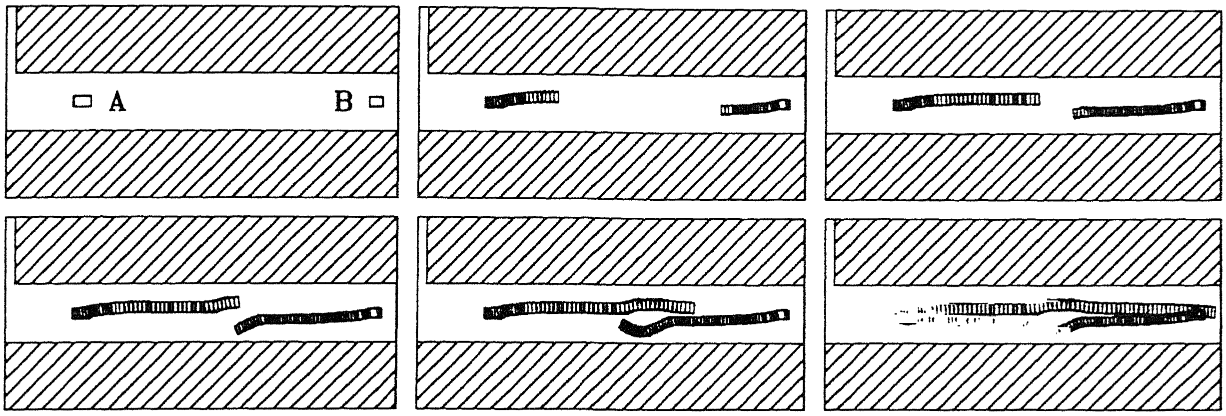


Figure 3.9: The simulation - Two vehicles of unequal Aggressiveness

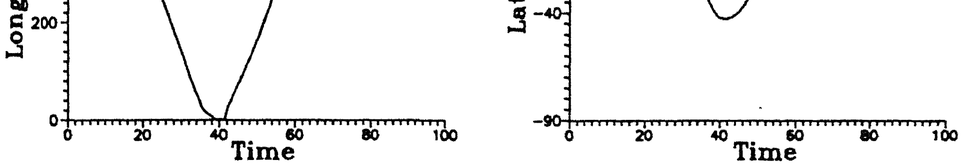


Figure 3.10: Characteristic Curves - Two vehicles of unequal Aggressiveness

3.2.6 A Rickshaw crossing a Truck

A rickshaw is moving in road. A truck approaches towards it.

Parameter	Value	
	vehicle A	vehicle B
Type of vehicle	Truck	Rickshaw
kgoal	7000	4000
kroad_near	300	200
kroad_far	2400	2000
kcar	50	250
kshadow_intersect	2000	5000
kshadow_non_intersect	50	50
Driver's Aggressiveness	100	10
Vehicle Size	6.75m × 3.75m	1.88m × 1.0m
Engine Power	600	50
Brake Power	700	60
Maximum Speed	54 kmph	11.25 kmph
Maximum Steering Angle	5°	15°

vehicle A		vehicle B	
x	y	x	y
10	250	600	250
650	250	25	250

Table 3.6: Parameters: A Rickshaw crossing a Truck
(a) The Vehicle and Driver Characteristics.
(b) The Path for the vehicles.(1 unit = 0.125m)

Analysis

The truck driver is much much aggressive than the rickshaw puller. So, the rickshaw puller moves aside to give the truck room. The lateral deviation of the truck is negligible. After the truck has moved away the rickshaw puller moves to its steady state configuration. The sudden diversion in the Time vs. Longitudinal Deviation curve is because of the fact that the truck has already reached its goal.

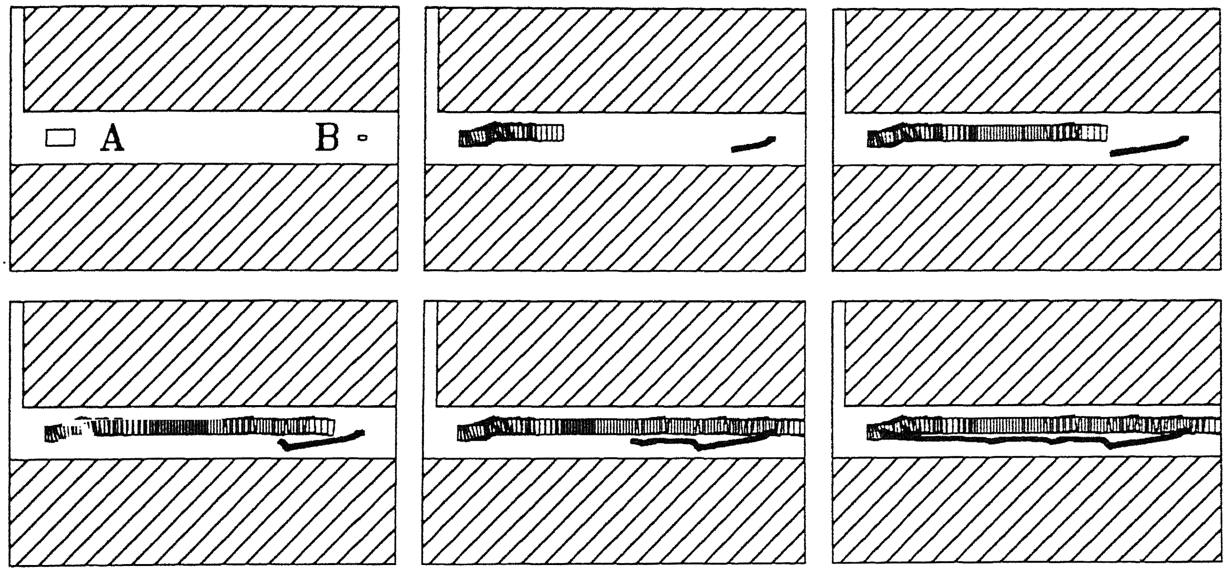


Figure 3.11: The simulation - A Rickshaw crossing a Truck

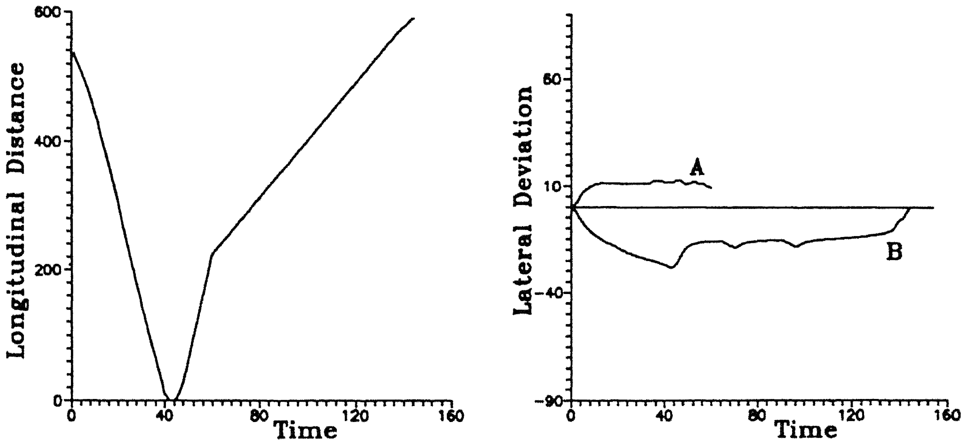


Figure 3.12: Characteristic Curves - A Rickshaw crossing a Truck

3.2.7 Vehicles in independent tracks

Two cars are in motion in independent tracks.

Parameter	Value	
	vehicle A	vehicle B
Type of vehicle	Car	Car
kgoal	7000	7000
kroad_near	300	300
kroad_far	2400	2400
kcar	100	100
kshadow_intersect	9000	9000
kshadow_non_intersect	150	150
Driver's Aggressiveness	60	60
Vehicle Size	4.5m $\times$ 3.0m	4.5m $\times$ 3.0m
Engine Power	550	550
Brake Power	600	600
Maximum Speed	45 kmph	45 kmph
Maximum Steering Angle	5°	5°

vehicle A		vehicle B	
x	y	x	y
-120	250	920	250
235	250	390	250
235	0	390	500

Table 3.7: Parameters: Vehicles in independent tracks
(a) The Vehicle and Driver Characteristics.
(b) The Path for the vehicles.(1 unit = 0.125m)

Analysis

Here the cars are motion in mutually independent tracks. The cars approach towards each other but before they reach that close, both of them turns to completely different tracks. None of the car trajectories shows any kind of sudden diversions.

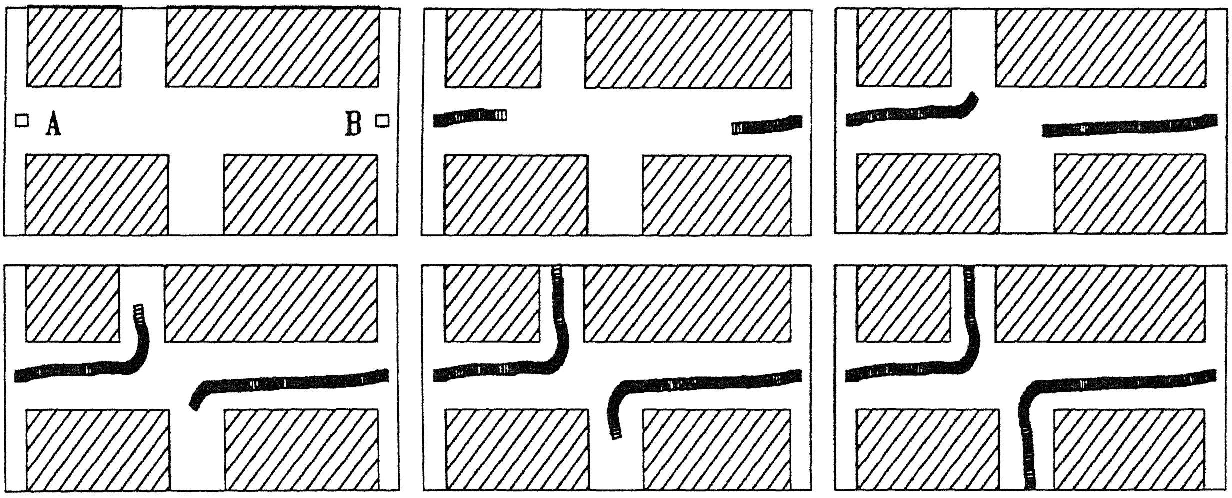


Figure 3.13: The simulation - Vehicles in independent tracks

3.2.8 Crossing and Turning

A car and a truck are approaching. They avoid collision, then both of them turn and continue to move.

Parameter	Value	
	vehicle A	vehicle B
Type of vehicle	Car	Truck
kgoal	7000	7000
kroad_near	300	300
kroad_far	2400	2400
kcar	100	100
kshadow_intersect	5000	5000
kshadow_non_intersect	50	50
Driver's Aggressiveness	50	100
Vehicle Size	4.5m × 3.0m	6.75m × 3.75m
Engine Power	550	600
Brake Power	600	700
Maximum Speed	45 kmph	54 kmph
Maximum Steering Angle	5°	5°

vehicle A		vehicle B	
x	y	x	y
750	250	-150	250
160	250	525	250
160	-25	525	525

Table 3.8: Parameters: Crossing and Turning
(a) The Vehicle and Driver Characteristics.
(b) The Path for the vehicles.(1 unit = 0.125m)

Analysis

Likewise Section 3.2.5, the diversions of the vehicles are different because the Aggressiveness index associated with the truck driver(B) is much higher than that of the car driver(A). Both the vehicles tend to move to their steady state

configuration before as well as after they cross each other. The turning is smooth and both vehicles decelerate before taking a turn.

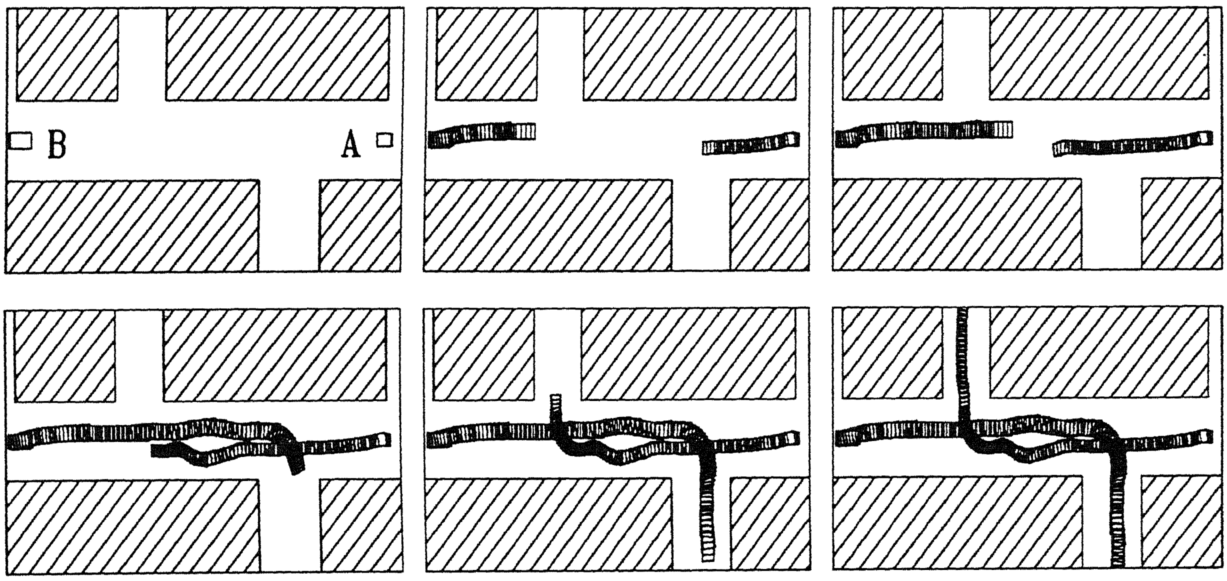


Figure 3.14: The simulation - Crossing and Turning

3.2.9 Overtaking and Turning

One car and a Truck are moving in the same direction. The truck overtakes the car from behind. Then both take turn and continue to move.

Parameter	Value	
	vehicle A	vehicle B
Type of vehicle	Car	Truck
kgoal	10000	10000
kroad_near	300	200
kroad_far	2400	1600
kcar	100	100
kshadow_intersect	9000	9000
kshadow_non_intersect	150	150
Driver's Aggressiveness	60	100
Vehicle Size	4.5m × 3.0m	6.75m × 3.75m
Engine Power	550	600
Brake Power	600	700
Maximum Speed	31.5 kmph	63 kmph
Maximum Steering Angle	5°	5°

vehicle A		vehicle B	
x	y	x	y
-30	250	-120	261
525	250	525	250
525	425	525	625

Table 3.9: Parameters: Overtaking and Turning
(a) The Vehicle and Driver Characteristics.
(b) The Path for the vehicles.(1 unit = 0.125m)

Analysis

Likewise Section 3.2.4, the truck(B) initially behind, overtakes the car(A). The aggressiveness of the truck driver is high and so he turns although the car is quite close to it while turning. The safer car driver further slows down to ensure a safe

turn for himself.

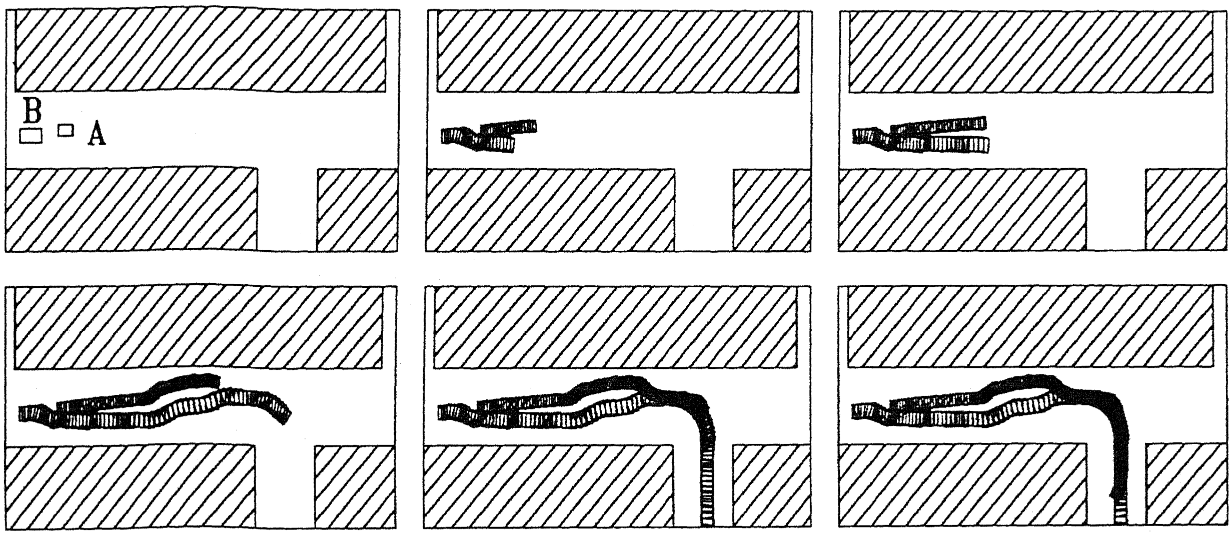


Figure 3.15: The simulation - Overtaking and Turning

3.2.10 Vehicles in intersecting zig-zag roads

Two cars are travelling in intersecting zig-zag roads.

Parameter	Value	
	vehicle A	vehicle B
Type of vehicle	Car	Car
kgoal	7000	7000
kroad_near	900	900
kroad_far	7200	7200
kcar	100	100
kshadow_intersect	9000	9000
kshadow_non_intersect	150	150
Driver's Aggressiveness	60	60
Vehicle Size	4.5m $\times$ 3.0m	4.5m $\times$ 3.0m
Engine Power	550	550
Brake Power	600	600
Maximum Speed	45 kmph	45 kmph
Maximum Steering Angle	5°	5°

vehicle A		vehicle B	
x	y	x	y
-20	375	215	-50
160	340	135	310
600	300	275	600

Table 3.10: Parameters: Vehicles in Intersecting Roads
(a) The Vehicle and Driver Characteristics.
(b) The Path for the vehicles.(1 unit = 0.125m)

Analysis

Both drivers have equal aggressiveness. However driver of car A is travelling faster and he crosses the road junction before B. Since B is a safe driver ($\mu = 60$) he slows down and deviates. Before the road junction the road where B travels has a turn. B turns according purely due to the potential field.

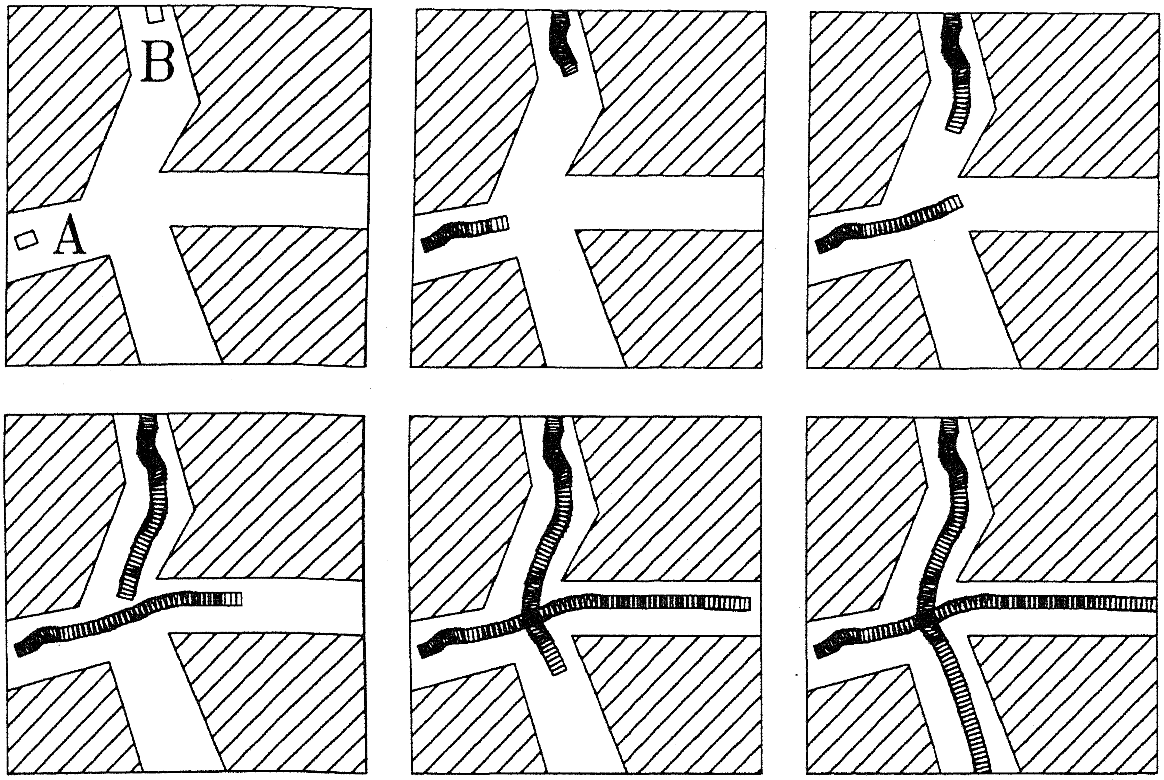


Figure 3.16: The simulation - Vehicles in Intersecting roads

Chapter 4

Conclusion

The the current work replaces conventional path-planning schemes involving explicit search. This is done by local decisions using potential field and driver behaviour based models. The results presented in Chapter 3 depict the suitability of the current work in modelling two vehicle interaction over a wide range of situations associated with congested roads with several turns and crossings.

Purely potential field based models cannot execute pre-planned motion sequences such as parking or "U" turning in narrow roads. However, these can be done by search based algorithms ([17], Figure 4.1). On the other hand, a purely search-based model is inefficient in handling conflicting dynamic situations. Thus, a trade-off between the two approaches is probably required. Such a model will use potential fields and in certain field characteristics it will also utilise some predefined set of possible actions - a feature of search-based algorithms.

However, the model presented in this thesis is elementary in nature and is based on potential field only. Further work needs to be done to model more complex and conflicting traffic situations. Some of the issues for future research can be:

Improved Agent Architectures based on "Belief"

The individual vehicle and its driver is modelled as an "agent" participating in the traffic (i.e., global) situation. Various agents of these nature interact between

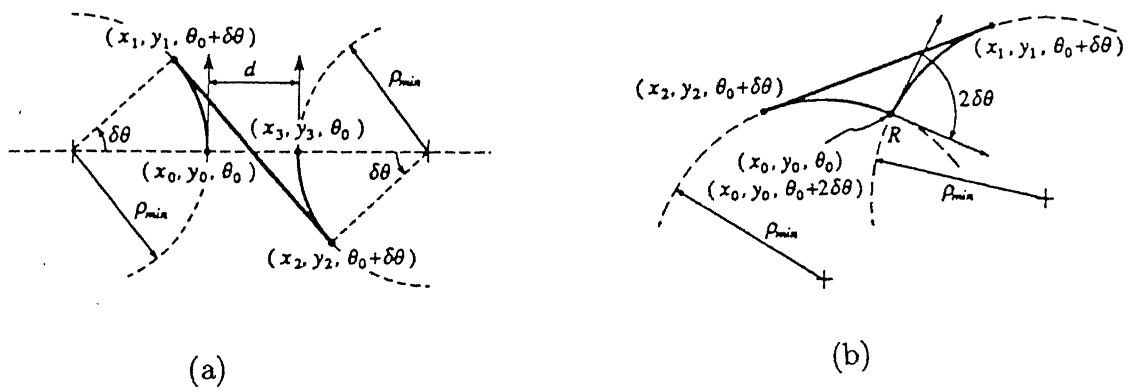


Figure 4.1: Typical maneuvering of vehicles in restricted space

(a) Parking Maneuver where the vehicle shifts sidewise with the initial position and final position changing without any change in orientation.

(b) Tight Turn Maneuver where the vehicle turns such that the initial position and final position remains same with change in orientation.

[Figure taken from Robot Motion Planning by J.C.Latombe - Fig. 5 & 6., Page 425]

themselves and also with the common environment [13] based on some shared beliefs about vehicle behaviour. This interaction however is not uniform because some agents may be reluctant to coordinate (a selfish driver) or unable to interpret correctly (an inexperienced driver) - these are open issues for further development of the belief based models. Beyond the simplistic numeric formalisms used here, symbolic or logic based formalisms [11] may be used for expressing more complex beliefs. Another important aspect is learning for advanced modelling of such agents. This requires the formulation of a metric for evaluating (and rewarding) the agent's (vehicle and its driver's) performance [15]. A rich knowledge base is also a pre-requisite for many of these issues.

Modelling for multiple vehicles

The obvious extension of the current work is to simulate a system with more than two vehicles of different types. In such model, the need for serving each of the participating vehicles simultaneously becomes essential. However, when all

the vehicles are in motion simultaneously, the C-Space for each vehicle changes rapidly and approximation becomes necessary. Efficient approximation of C-Space is a function of the driver's belief regarding the motion of other vehicles. When three or more vehicle come very close to each other, this issue becomes particularly relevant. To minimise the error of misinterpreting the C-Space, motion should be planned for a very small time step.

More complex Modes

The special maneuvering (as shown in 4.1) schemes can be included as modes and can be executed when a given set of pre-conditions exist.

Improved Look-ahead Model

The current Look-ahead model can be extended so as to generate a shadow for the other vehicle too. This, along with some high level belief can be used to estimate the motion of the other vehicle particularly at the crossings.

Improvement in Simulation/Implementation

There is need to generate the simulation in real time execution. Also there is need to develop algorithms to take care of non-convex vehicles and road edges. Agents (ie, vehicle and its driver) can be modelled as separate modules with a finite set of information (local) available to them. This modularisation leads to a better representation of belief-based architectures.

Validation of the results

The results obtained from the model should be compared with the real road and vehicle data and accordingly tuning of the parameters or modification of empirical relations can be made.

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